Interdisciplinary Excellence Accelerator Series

Christian Brecher · Günther Schuh
Wil van der Aalst · Matthias Jarke
Frank T. Piller · Melanie Padberg *Editors*

Internet of Production

Fundamentals, Methods and Applications

INTERNET OF PRODUCTION | RWTH AACHEN UNIVERSITY

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Interdisciplinary Excellence Accelerator Series

Series Editors

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The Interdisciplinary Excellence Accelerator Series (IDEAS) is an innovative book series highlighting interdisciplinary and excellent research conducted at universities, such as the ‘Cluster of Excellence’ at RWTH Aachen University, Germany, and their collaborating partners across the world. The series enables a new form of fast publication anchored in the spirit of interdisciplinary collaboration from authorship to review to dissemination.

These high-quality books can be used by scientists, practitioners, and students for different purposes ranging from teaching to research and knowledge transfer. The series contains both English and German-language books, and focuses on fields such as, but not limited to:

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With 160 Figures and 4 Tables

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Preface

Crossing Disciplinary Boundaries: RWTH Aachen and Springer Start a New Publishing Partnership

This first volume of the new Interdisciplinary Excellence Accelerator Series (IDEAS) is the first major outcome of more than a year of joint work with its inception in a 2-day publishing lab workshop with researchers from the Excellence Cluster "Internet of Production" at RWTH Aachen (Germany) and editors from Springer held in March 2021. The aim of the online event was to understand current researcher needs and pain points, as well as exploring ideas for potential solutions.

The event was well prepared – including a survey which RWTH Aachen addressed to students and researchers at their Cluster of Excellence – and eventually centered around two main themes in research and publishing:

- How to accelerate the journey from research to publication and scholarly knowledge transfer?
- How to facilitate truly interdisciplinary research and publishing?

In what follows, we put forward the three tenets which the participants of this workshop have agreed upon as the way to encourage, enhance, and propagate accelerated interdisciplinary work.

Tenet 1: Reduce the Time Between Research, Publication, and Scholarly Knowledge Transfer

Scientific research has accelerated dramatically over the last decades. This is not only a consequence of the rise of digital technologies and the Internet. Emergencies such as the Covid pandemic and the climate crisis have also increased the political and public demand for faster research outcomes. The development of effective Covid-19 vaccines in less than one year after the pandemic hit can be considered as an impact of such demand.

On the academic side, researchers with good reason would say: *If you want us to produce research results faster, then you have to provide us with the appropriate tools, resources, and dissemination infrastructure.*

Academic publishers have not always fully understood current researchers' needs in their actual lab and scholarly environments. Particularly, it takes too much time for research results to become available in the scholarly knowledge transfer and teaching. One can highlight this by pointing to textbooks which, in many cases, take between 3 and 5 years from conception to their release. By that time, the presented research results and data are often outdated already. This might have been fine in former decades with a much slower pace of the research progress. In a time of accelerated research, this is not fast enough anymore which is a severe problem.

At the publishing lab, we clearly addressed that research publishers need to find solutions to bring current research outcomes into the scholarly knowledge transfer and academic teaching with a much faster turnaround. And there are a number of ways to do so:

- An "Online First" publication may be one part of the mix.
- Solutions to provide researchers, teachers, and students with the ability to compile and recompile their material themselves according to current status and requirements may be another part.
- Keeping content up to date in a more continuous way instead of publishing new editions every 3 to 5 years is yet another component.

Many of such partial solutions already exist, yet the challenge is to combine them in a smart and convenient way – also balancing the classical triangle of time, quality, and value – so they have a positive impact on scholars.

Tenet 2: Make Interdisciplinary Review Mandatory

The second major theme of the publishing lab was the interdisciplinary aspect of research. It is a matter of fact that the global challenges of our days require researchers to overcome the boundaries of the discipline silos. In consequence, the Cluster of Excellence "Internet of Production" at RWTH Aachen puts a particular focus on interdisciplinary research: "With the Internet of Production, our vision is to enable a new level of cross-domain collaboration" (https://www.nature.com/articles/d42473-019-00089-5).

Yet, the reality in research and publishing does not always fit with such demand for interdisciplinary research as we discussed at the publishing lab:

- Although it is often quite clear which academic disciplines are required to collaborate on a given field of problems, it is a common experience that putting researchers from different disciplines at one table is not sufficient as they might not understand each other due to the languages, jargons, and even the academic approach specific to their disciplines.

- While interdisciplinary research is the order of the day, research communities tend to prioritize and reward the outcomes and publications within their own disciplines rather than interdisciplinary work.
- Research methods and data frequently stay within their discipline boundaries instead of being mutually shared between the disciplines, where applicable.
- Existing publishing formats do not intrinsically encourage researchers to cross the bridge to other disciplines.

The discipline silos also become apparent when it comes to peer-review. Peer-reviewers, by the nature of their remit, may not bridge the gap between the disciplines and at the same time, cross-discipline[1] reviewer recommendation is not a common feature in peer-reviewer finder tools either.

In the ideal world of the Excellence Cluster "Internet of Production," the reality would look as in this simplified example:

1. A researcher in Mechanical Engineering shares research data from the lab.
2. A Computer Scientist reviews the data and writes an analysis.
3. A Social Scientist reviews the analysis and writes a reflection.
4. Every single step is published and adds to researchers' credits.
5. All three pieces together (points 1, 2, and 3) make up for the final research publication.

We also thought about where exactly do people from different domain backgrounds come together and actually talk to each other as well as jointly experiment on their ideas. In the IT and tech domain, this is common practice and is termed "hackathons." So why not establish dedicated peer-review events that follow a cross-domain approach such as hackathons do. Such events would also accelerate the reviewing itself. And more than that, events like this might over time help cultivate a language that different disciplines understand and which would also help building interdisciplinary communities and allow cross-discipline application of methods hitherto used in siloed disciplines only.

Tenet 3: Use books as calls to action and solution vehicles

This first book of the Interdisciplinary Excellence Accelerator Series (IDEAS) is a starting point. It is composed of chapters each of which has been prepared by an interdisciplinary research team. In the spirit of agile development, we want to iterate over the course of the next 2 to 3 years in order to introduce a new way of collaboration (including dedicated review events) together with a new research

[1] In this introduction, the terms "cross-discipline" and "interdisciplinary" are being used interchangeably.

publishing format which we call *Crosstracts*. It is this new concept of *Crosstracts* which will allow researchers to:

- Find potential collaborators at an early research stage
- Publish research and research data early and faster
- Recognize the various stages of the knowledge and manuscript creation
- Make interdisciplinary review and feedback mandatory, collaborative, and transparent in a novel and constructive manner
- Facilitate interdisciplinary research with a positive impact on global challenges and societal recognition
- Boost the creation of cross-discipline communities with a language and knowledge configuration that all participants understand
- Resulting in a cross-discipline book series that is engineered in such a way that it crosses the boundaries of single disciplines with a much earlier re-usability in the scholarly knowledge transfer (in German: "*akademische Lehre*")

There is a reason why we decided to begin with a book series. First of all, books are a great opportunity to experiment, iterate, and adjust on the way forward. But there is more to it. Books have an impact both on the consumption side – i.e., for their readers – as well as on the side of their creators. The various existing book categories – such as monographs, handbooks, textbooks, encyclopedias – all require their authors to create them in a specific way. In consequence, books are not only helping their readers to achieve certain goals, e.g., passing exams. Books are increasingly also specific calls to action toward their authors themselves.

This is exactly what a *Crosstracts* book series wants to achieve: Make it obligatory to interdisciplinary research teams to not only collaborate but also mutually review each other's research and hence truly understand and influence each other, so *the whole of their interdisciplinary research becomes greater than the sum of their discipline-specific parts*. In that very sense, books are not only representing research outcomes to an audience. They are also an excellent solution vehicle for research teams in general.

It is a beginning of the change which academia has always been seeking, and it is an ongoing process. We call upon readers of this publication to come forward and suggest further improvements, ideas, or initiatives to contribute to a new reality of truly interdisciplinary, fast, and impactful scholarly knowledge transfer.

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Editorial

With the Cluster of Excellence Internet of Production (IoP), more than 200 scientists from the fields of production engineering, computer science, materials engineering, social science, and business administration are simultaneously facing up to the task, but also the obligation, of addressing future challenges and goals for production technologies with all their facets to generate innovative solutions and practical concepts to shape the production of tomorrow.

The vision of the IoP is to identify relevant data from production, development and use in real time, select, and reduce it in a form that it can be used adequately by solving interdisciplinary tasks and thereby provide the decisive research impetus for shaping the future of digitalization in production engineering. This involves industrial artificial intelligence, advanced manufacturing and materials, intelligent data infrastructures, and a holistic view of the future of work. This means the main task is to derive and create real added value from the gigantic amounts of data that already exist in all areas of production – for the entire production itself, the individual machine, and all the people involved – described by transferring the IoT to the world of production.

Interdisciplinary publishing presents us with major challenges. What is already "state of the art" for some is applied in another discipline new research for others. By linking topics that have already been researched in different disciplines, new fields of research emerge as limitations are re-challenged. Each discipline has its own language, styles, and requirements for scientific publishing. Whereas in one discipline the description of applications and use cases is mandatory, in others they are considered to be delicate or even frowned upon. And even the internal review process, with different disciplines looking at each other, cannot always be fully transferred to the topics. Often, no direct feedback on the work can be given, but rather a new perspective can be shown, an outlook on upcoming topics can be considered, and a dialog is created that requires and enables a view beyond one's own focus.

Fortunately, together with Springer, we were given a unique opportunity to understand and approach publishing in a new way. We developed a new series called Interdisciplinary Excellence Accelerator Series (IDEAS). The series enables a new form of fast publication anchored in the spirit of interdisciplinary collaboration from authorship to review to publication. The resulting high-quality books can be used both by academics and practitioners for different purposes ranging from teaching to research and knowledge transfer. This book is the first of this series.

To provide a fast publication process and taking in account that most readers only read certain chapters of their interest, the individual chapters of the book are intended to stand on their own. The book is intended to provide an overview of the challenges of tomorrow's production technology and describe initial approaches to solutions along the way.

This book presents and summarizes the interim results of the Cluster of Excellence during the first half of the funding phase under the Excellence Strategy. For more detailed results, reference is made to corresponding scientific publications. An update with further research results will follow.

We would like to thank all scientists for their extraordinary commitment and excellent results, as well as the German Research Foundation (DFG) for funding the Cluster of Excellence "Internet of Production" in the funding period of the Excellence Strategy.

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Aachen
May 2023

Prof. Christian Brecher
Prof. Günther Schuh
Prof. Dr. Wil van der Aalst
Prof. Matthias Jarke
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Prof. Dr.-Ing. Christian Brecher has held the Chair of Machine Tools at RWTH Aachen University since January 2004. His research areas include machine technology, machine data analysis and NC technology, control technology and automation, gear technology, precision machines, fiber composite technology, and integrative lightweight construction. At the same time, he became a member of the Board of Directors of the Laboratory for Machine Tool and Production Engineering (WZL) and of the Fraunhofer Institute for Production Technology IPT in Aachen.

From 2006 to 2018, Prof. Brecher was spokesperson for the Cluster of Excellence "Integrative Production Technology for High-Wage Countries" at RWTH Aachen University. In 2012, he founded the Aachen Centre for Integrative Lightweight Production (AZL) together with Prof. Hopmann. In 2018, Prof. Brecher was appointed Director of the Fraunhofer Institute for Production Technology IPT. Currently, Prof. Brecher is also, among other positions, spokesperson for the Cluster of Excellence EXC2023 "Internet of Production" (IoP) at RWTH Aachen University, spokesperson for the SFB/Transregio 96, Fellow of the International Academy of Production Engineering (CIRP), and member of the German Academy of Science and Engineering (acatech). In 2020 and 2021, he was President of the Scientific Society for Production Engineering (WGP).

Prof. Dr.-Ing. Dipl.-Wirt. Ing. Günther Schuh has held the Chair of Production Engineering at RWTH Aachen University and is a member of the Board of Directors of the Laboratory for Machine Tools and Production Engineering (WZL) of RWTH Aachen University and the Fraunhofer-Institute for Production Technology (IPT) in Aachen. He is also Director of the Research Institute for Industrial Management at RWTH Aachen University (FIR e. V.). Additionally, he is one of the deputy spokesperson of the Cluster of Excellence "Internet of Production" at RWTH Aachen University. In 2005, Prof. Schuh initiated the RWTH Aachen Campus, a network of science and business with currently more than 420 technology companies.

As a scientist and entrepreneur, Prof. Schuh is concerned with disruptive innovations, information and production management, as well as sustainable mobility solutions. He supports the approach that complex interrelationships and systemic innovations require scientific and entrepreneurial collaboration. For more than 30 years, he has been working on issues of innovation and technology management, industrial production, and complexity management in industrial systems. With researchers and developers in the industry, he has repeatedly proven to develop cost-effective industrially manufactured products, especially electric vehicles, with Industry 4.0-based highly iterative development processes as well as new product and production architectures. In order to implement new mobility concepts into practice, he is still the founder of various companies that develop and produce mobility solutions. The focus is on holistic solutions to drive the transformation to new individual transport.

Prof. Dr. Ir. Wil van der Aalst is Full Professor at RWTH Aachen University, leading the Process and Data Science (PADS) group and deputy spokesperson of the Cluster of Excellence "Internet of Production" at RWTH Aachen University. He is also the Chief Scientist at Celonis, part-time affiliated with the Fraunhofer FIT, and a member of the Board of Governors of Tilburg University. His research interests include process mining, Petri nets, business process management, workflow management, process modeling, and process analysis. Wil van der Aalst has published over 900 articles and books and is considered to be in the top-15 of most cited computer scientists with an H-index of 170 and more than 130,000 citations.

Van der Aalst is an IFIP Fellow, IEEE Fellow, ACM Fellow, and received honorary degrees from the Moscow Higher School of Economics (Prof. h.c.), Tsinghua University, and Hasselt University (Dr. h.c.). He is also an elected member of the Royal Netherlands Academy of Arts and Sciences, the Royal Holland Society of Sciences and Humanities, the Academy of Europe, and the North Rhine-Westphalian Academy of Sciences, Humanities and the Arts. In 2018, he was awarded an Alexander-von-Humboldt Professorship.

Prof. em. Dr. Matthias Jarke is Professor em. of Databases and Information Systems at RWTH Aachen University. After his Doctorate from Hamburg University in 1980, he held professorships at the Stern School of Business at New York University and the University of Passau before joining RWTH in 1991. Key teaching contributions focus on RWTH internationalization, founding the Bonn-Aachen International Center for IT (b-it) and as Inaugural Dean at the GUTech German University of Technology in Oman. After 8 years as Chairman of Aachen's CS Department, he became Executive Director of the Fraunhofer Institute for Applied Information Technology FIT. As ICT representative in the Fraunhofer Presidency 2010–2015, he co-initiated the International Data Space concept for European data sovereignty.

Jarke's research addresses database query processing, metadata management, requirements, and information systems engineering. Large interdisciplinary projects studied Chemical Engineering processes, Media and Cultural Communication, and Highspeed Mobile Information and Communication. Currently, he serves as deputy spokesperson of the Cluster of Excellence "Internet of Production" at RWTH

Aachen University. As President of the GI German Informatics society, Jarke coordinated the BMBF Science Year 2006, which started the German Chancellor's Digitalization Summits. He was elected to the German Academy of Technology and Sciences acatech and received prestigious awards including ACM Fellow and GI Fellow.

Prof. Dr. rer. pol. Frank T. Piller is Professor of Management and Head of the Institute for Technology and Innovation Management at RWTH Aachen University. Prior to that, he had positions at MIT and TU Munich. He is also the Academic Director of the Institute for Management Cybernetics (ifu e.V.), an independent research institute associated with RWTH Aachen with a focus on applied machine intelligence, systemic change, and institutional transformations. Prof. Piller's current research focuses on the need of established corporations to deal with disruptive business model innovation and supporting organizational structures and cultures. Leadership for Industry 4.0 and Managing a Digital Transformation are core topics in this field. He also is currently building a research program on the role of AI&ML in the innovation process and managing hybrid innovation teams, where human experts and algorithms/machines collaborate ("hybrid intelligence"). Prof. Piller is a Principal Investigator in the Cluster of Excellence "Internet of Production" at RWTH Aachen and serves as a scientific advisor to Germany's national Industry 4.0 policy. Prof. Piller has consulted with many Dax30 or Fortune500 companies and serves as an advisor for several deep-tech startups.

Melanie Padberg, M.Sc., received the B.Sc. degree in Mechanical Engineering and the M.Sc. degree in Automation Engineering from RWTH Aachen University, Aachen, Germany. After her graduation, she started as a researcher within the Chair of Machine Tools at the Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University. Her research focused on automation and safety in the Industrial Internet of Things, and cloud and edge computing as enabler for the digital shadow.

Since January 2022, she is Managing Director of the Cluster of Excellence "Internet of Production." In her position, she is responsible for the comprehensive scientific coordination of the Cluster of Excellence and its sustainable personnel, scientific, and structural development.

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Part I

Introducing the Internet of Production

The Internet of Production: Interdisciplinary Visions and Concepts for the Production of Tomorrow

1

Christian Brecher, Melanie Padberg, Matthias Jarke, Wil van der Aalst, and Günther Schuh

Contents

Abstract

Changes in society require changes in our industrial production. In order to remain competitive in the future, the masses of data available in production must be used urgently. This is still a challenge because data are often not accessible or understandable. Therefore, we developed the Internet of Production (IoP) concept which aims to collect, unify, and exploit different data sources and improve production. To this end, the various research domains of production technology,

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the need for a common infrastructure, and the concept of the Digital Shadow are presented. The vision can only be achieved through interdisciplinary cooperation between different disciplines. Therefore, the joint approach is explained and common research topics are presented. Interdisciplinary cooperation is the key for further steps to achieve the common vision.

1.1 Introduction

Production technology plays a central role in our economy. In order to avoid overcapacities and overproduction, to keep production in high-wage countries attractive, and to meet the needs of customers for more individuality of products (mass customization), a stringent digitalization of all production assets connected with production and the continuous involvement of the employee is necessary (Brecher et al. 2017). Even though this development has been observed for a long time under the term Industry 4.0, few digital solutions have been used in industry so far, and, in particular, end-to-end networking from the shop floor to the office and data exchange across company boundaries is still not feasible. Although large amounts of data are available in production technology, they are often inaccessible, uninterpretable, or incomplete. This can have technical and organizational causes, as can be witnessed in many projects. Either technical hurdles, such as the selection of suitable protocols and databases to provide data, or organizational hurdles, such as ensuring the reusability of data, are addressed. However, the larger vision of universally available data enabling new business models takes a back seat. A lack of trained staff and dealing with new risks also pose major challenges for companies.

The internet and approaches such as the Internet of Things (IoT) have revolutionized the availability of data and knowledge (Schuh et al. 2019). Therefore, advances under the terms such as *Industry 4.0*, the *Industrial Internet of Things* (IIoT), and *Made in China 2025* have been made to combine technological advances in Internet and Communication Technologies with the production technology (Jeschke et al. 2017; Mueller and Voigt 2018). However, these concepts cannot be transferred holistically to production technology. The number of parameters in production plays a decisive role here. So for knowledge to be generated from data in the production context, these data sources need to be extremely networked, contextualized, aggregated, and processed. An *Internet of Production* is necessary. The following vision was defined for this:

> The vision of the Internet of Production (IoP) is to enable a new level of cross-domain collaboration by providing semantically adequate and context-aware data from production, development and usage in real-time, on an adequate level of granularity.

The IoP pursues the idea of laying the foundation for a World Wide Lab in which production engineering models can be used across domains (Schuh et al. 2019; Kappel et al. 2022). The research project therefore connects material engineering with production technology and management on all life cycle phases through a digital infrastructure and business modeling. Each operation carried out is a potential experiment. New insights can be gained from the data provided. For this, an infrastructure must be created that connects data from different production domains, makes the data usable through modeling and aggregation, and provides algorithms for extracting knowledge. Therefore, we developed new data science approaches and artificial intelligence techniques ranging from reinforcement learning to process mining. At the center of the IoP is the human being who orchestrates the production technology (Brauner et al. 2020). This requires a new kind of collaboration between different disciplines: building on a strong link between production technology, materials science, and information technology, the production technology of tomorrow can be designed with the help of various sub-disciplines of the social sciences and management.

The necessary interfaces between the different research domains, a detailed presentation of the vision and the concepts (see Sects. 1.2 and 1.3), and the first success reports of the interdisciplinary research (see Sect. 1.4) are presented in the following sections.

1.2 Research Domains in Production

In order to take a holistic view of production technology, the three life cycle phases of development, production, and use must be considered:

Development (Fig. 1.1): Product development is always at the beginning of production. Increasingly, however, it is becoming more and more iterative, based on findings from production and use. Agile product development is therefore strongly intertwined with three processes and methods: market development, prototype engineering, and production. The goal is to radically reduce lead time while at

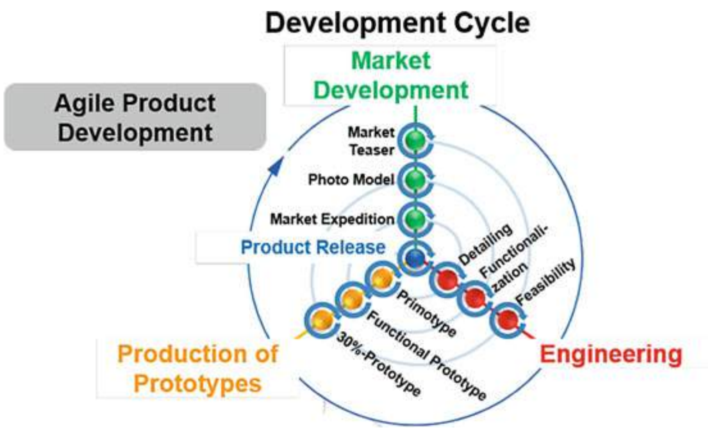

Fig. 1.1 Dimensions of the development cycle

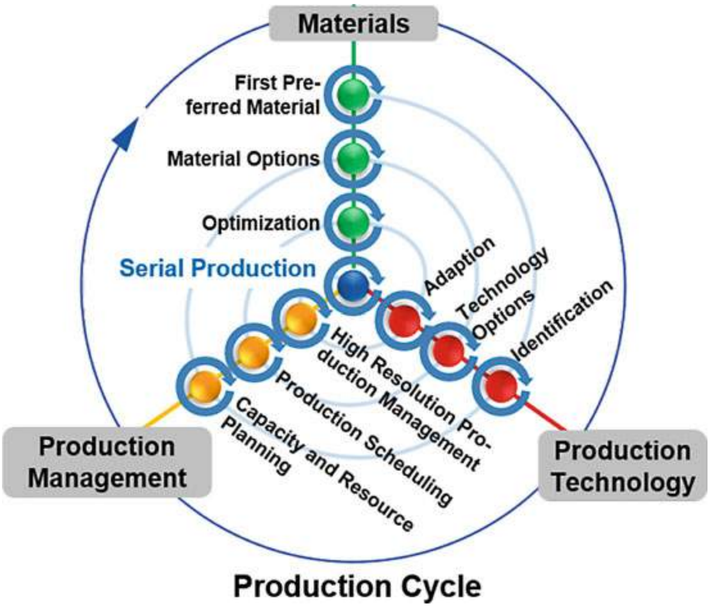

Fig. 1.2 Dimensions of the production cycle

the same time exceeding customer expectations. To establish new processes and methods, organizational structures must be investigated and data structures must be developed to overcome semantic conflicts and performance latencies. In addition, technologies for prototyping are needed, which in turn support the agile adaptation of the product with the help of process data. A minimum viable product together with relevant data provided by the IoP enables continuous stakeholder involvement and cross-domain collaboration.

Production (Fig. 1.2): Within the production cycle, there are three essential sub-areas that only lead to high-quality products in harmony with each other: the consideration of materials, production technologies, and production management. The goal is to create an environment in which the production system can act adaptively despite uncertainties. For this purpose, data from all areas with their metadata must be made available across domains. The selection and use of materials forms the basis of the production process. Therefore, it is all the more important to incorporate findings from the production process and use into the selection of the material. For a longer service life, dynamic production scenarios and condition monitoring of components can be included. Adaptive production requires the reduction and composition of heterogeneous engineering models of production technologies to be able to analyze data from production in real time. This enables production management to make faster and better decisions to adapt highly specialized processes at all other levels of the company.

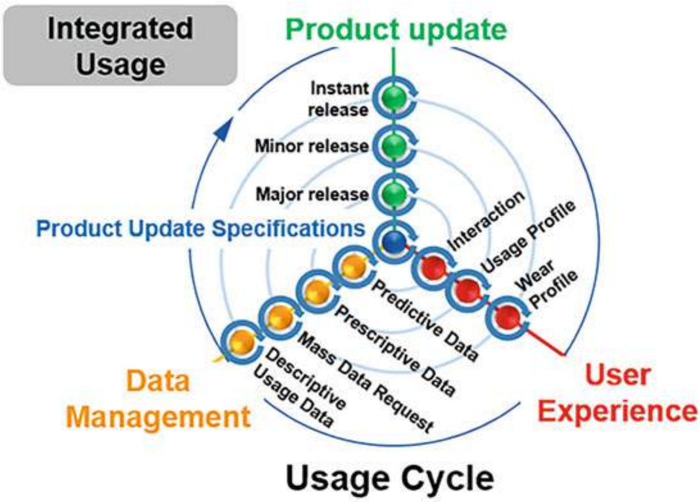

Fig. 1.3 Dimensions of the usage cycle

Usage (Fig. 1.3): The usage phase of the products and equipment should bring new insights for the development and production of products. Networked data, products, and equipment generate added value. This means that products and equipment must also provide data during usage. Moreover, many manufacturers engage crowdsourcing of critical feedback and innovative ideas from premium user communities. Through holistic data management with the help of descriptive, prescriptive, and predictive mass data, product update specifications can be created and thus the product can be regularly renewed. In addition, human interaction with the product, the equipment, and associated services can be improved. Interfaces to the technical systems need to be developed that contribute to the development of capabilities, the evolution of organizational structures, and the selection of an appropriate governance mode. Production systems become more transparent to people. This is achieved through an internal view, which deals with the cooperation of the human with the technical system, and an external view, which deals with possible platform and business models.

Following the discussion above, the IoP Cluster of Excellence has been organized in five Cluster Research Domains (CRDs): one for the development perspective (Fig. 1.1), one for usage (Fig. 1.3), and one for each of the three dimensions of the production cycle (Fig. 1.2). Each of the CRDs is further subdivided in work streams in which interdisciplinary teams address specific research challenges or use cases.

Moreover, all three domains have one thing in common: they need an open, shared infrastructure to unfold their potential. Therefore, a conceptual, physical, and functional infrastructure has to be developed that connects all major domains of networks of companies within a World Wide Lab in the future. The World

Wide Lab should enhance a cross-company and international division of labor and cooperation for mutual learning from dependencies. Moreover, to ensure resilience, we need to carefully manage dependencies and limit the outflow of knowledge. The infrastructure must enable the execution of multi-agent models and data streams in distributed communication networks within and between layers while guaranteeing the required performance, reliability, security, and safety at all levels. In order to be able to use the extremely heterogeneous production data in a cross-domain manner, knowledge graphs (e.g., Noy et al. 2019) must be provided with data sources that provide the user with access and the data structure, as well as the context. In order to generate new, cross-domain knowledge from the data, reduced models must be combined with data-based algorithms and thus enable context-adaptive actions. In the future, it can be assumed that the domains will merge more and more. With the existing data and new cooperation between companies, new business models can be established that disruptively change production technology in its processes and organization. Furthermore, in the context of the circular economy (Riesener et al. 2019), the life cycle phases will no longer run sequentially with individual information returns. Rather, the life cycle phases will close in a circular fashion. Extensive knowledge about the history of individual components is therefore required in order to be able to feed them into an R-cycle. The basis for this can only be provided by the IoP, which includes all life cycle phases and provides an open, common infrastructure.

1.3 Objectives of the Internet of Production

To make cross-domain data access and cross-domain models user-friendly for a growing number of experiments throughout the World Wide Lab, we developed the concept of the Digital Shadow. In the growing literature on Digital Twins (Bauernhansl et al. 2018; Jones et al. 2020), Digital Shadows are often interpreted as the data supply link from the physical systems to their Digital Twins. However, this is only one of the aspects why Digital Shadows are important. As Fig. 1.4 illustrates, a World Wide Lab would host a huge variety of reusable Digital Shadows as condensed knowledge integrating reduced mathematical models with captured data from all phases and domain-specific perspectives, ranging from very small (materials science) to very large (worldwide management). The network of Digital Shadows thus constitutes the conceptual core of the IoP infrastructure.

Digital Shadows (Jarke et al. 2018) are based on recorded raw data streams – for example, heterogeneous production, development, or usage data. These data are transformed into knowledge with the help of production models. For this purpose, the data must be semantically processed, and an application-specific aggregation of the data of all domains relevant to the problem must be carried out in a task-specific granularity. To this end, the domain-specific knowledge, which is provided through mathematical or physical models or established standards, is extended with data-driven models with the aim of formalizing knowledge and acquiring new

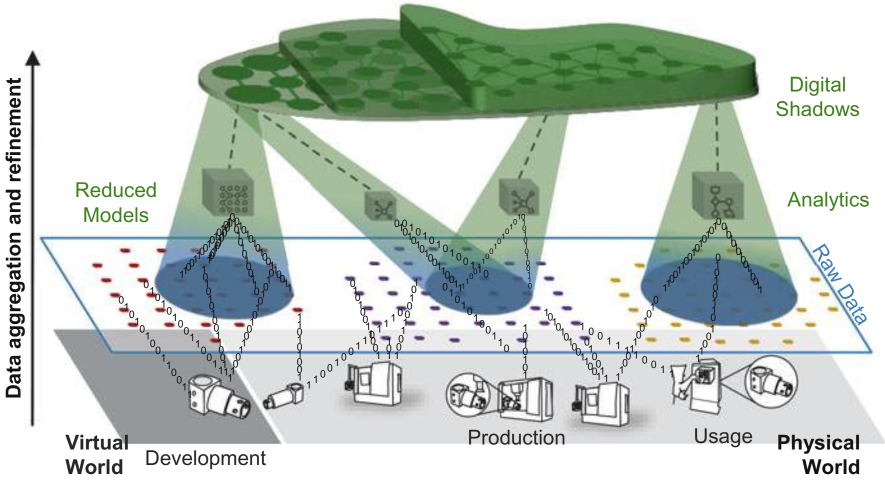

Fig. 1.4 Digital Shadows in the Internet of Production (Jarke et al. 2018)

knowledge in order to provide recommendations in real time. The Digital Shadow enables different views to be taken and is continuously being developed. In this way, parallels between different use cases are to be found and knowledge transferred between domains.

In order to be able to implement the concept of the Digital Shadow, the infrastructure (Schuh et al. 2017) in production technology must be understood and expanded. The raw data in production engineering is heterogeneous, often unstructured, and application-specific. They are created in highly specialized software, machines, or sensors for which no uniform formats are defined. Therefore, an action layer is needed to handle these heterogeneous, highly voluminous, distributed data streams from production and to make them available in a seamlessly interoperable way. Based on this, a layer is needed to process the data (Smart Data). The data is described by means of comprehensive data models and processed and made available in a real-time and context-sensitive manner. By combining abstract and structured knowledge, the data is transformed into new insights using advanced analysis methods (e.g., process mining and other machine learning techniques). These new insights are made available to the experts as intuitive and interactive decision support (Smart Expert). Therefore, advanced engineering tools have to be developed in order to integrate new data-driven models.

It is not enough to describe the infrastructure theoretically: it must rather be implemented in direct application in the research and industrial environment. The Digital Shadow must not remain a concept. Hurdles must be jointly identified and removed through interdisciplinary cooperation. As Fig. 1.5 shows, interdisciplinarity is the key to the vision of the IoP.

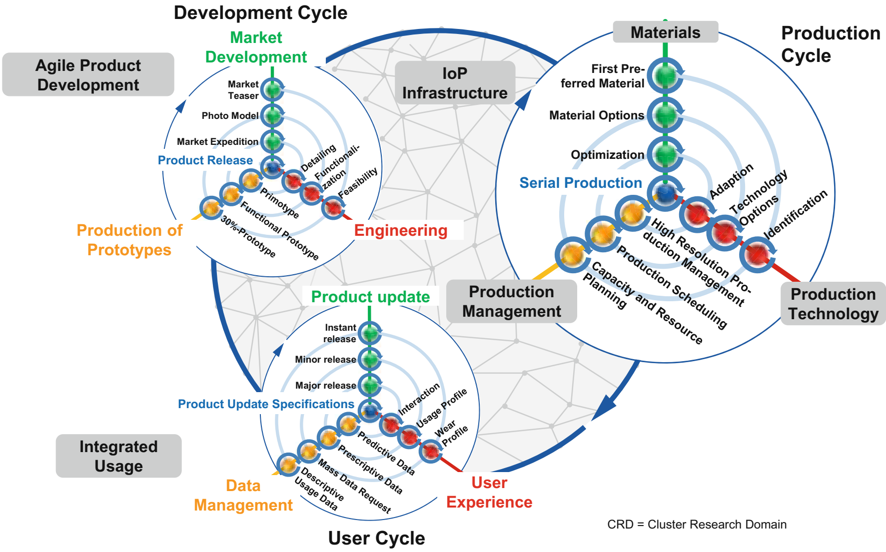

Fig. 1.5 Fostering the cycles onto the IoP infrastructure

1.4 Fostering Interdisciplinary Research for the IoP

Interdisciplinary cooperation has grown over the years. Different scientists look at particular challenges in their domains (e.g., Niemietz et al. 2021) and gradually expand their solution space to other domains or disciplines (e.g., Kunze et al. 2021). It is a development from mutual empowerment, via linked research work, to converging issues of different domains. Figure 1.6 illustrates how the Cluster of Excellence IoP is organizing this challenging process in three major stages – across over 30 research institutes together with many external partners. In addition to getting external partners involved in specific use cases or by leveraging commercial platforms, intense debates in a comprehensive Delphi study (Piller et al. 2022) have instigated further research challenges and hypotheses to be further explored in the time range up to 2030.

In relation to the production domains, this means in many cases that the scientist identifies a problem and first collects data with the help of internal or external sensors. This data is usually processed and stored. Afterward, various data-driven algorithms (e.g., in combination with physical models, Brecher et al. 2022) are used to gain new insights. On this path, a first interdisciplinary exchange is already necessary, since the scientists have to think about the suitable infrastructure in addition to the actual production-technical problem, which is not trivial for each application (Pennekamp et al. 2019). The number of available technologies for networking production plants and algorithms is unmanageable and is constantly evolving, and the optimal use of suitable parameters poses a great challenge to scientists (e.g., Rom et al. 2022).

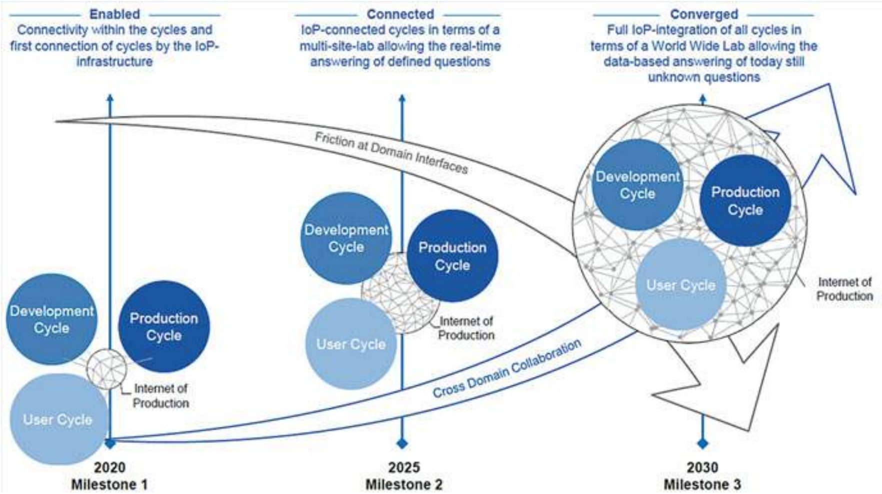

Fig. 1.6 Fostering interdisciplinary research: three stages of the Internet of Production

Technologies from the field of computer science are thus becoming enablers of production technology research. Organizing World Wide Labs requires contributions from different disciplines (Brauner et al. 2022), such as the deep intertwining of reduced physical models and their context adaptation by machine learning from data streams in Digital Shadows (Liebenberg and Jarke 2020); ensuring data quality and reusability of Digital Shadows by detailed provenance information (Becker et al. 2021); developing policies for sovereign data exchange across organizational boundaries (Jarke 2020), supported by industry-specific security and privacy technologies (Pennekamp et al. 2021); and the networking of individual Digital Shadows for the analysis of larger cooperation contexts, such as supply chain analysis, transfer learning across use cases (Baier et al. 2022), and process mining which provides techniques for process discovery, compliance checking, and predictive process analytics (Abouridouane et al. 2022; van der Aalst et al. 2021).

With the help of mutual enabling, a mutual understanding of the domains under consideration is created. The next step is to develop a common language (e.g., Mertens et al. 2022). With the help of this common language, common questions can now be developed. This is a central step for the development of a World Wide Lab. The concepts from computer science should not simply be applied to the production technology infrastructure. Commonalities and mediating data layers must be established that enable a real transfer between different domains.

To foster interdisciplinary research, the research program is extended with structural objectives. A Research School hosts different measures to give the researchers orientation inside the Cluster of Excellence. Internal and external conferences are organized to give the researchers the opportunities to have regular exchange regarding their research ideas and outcomes. In Research Summits, researchers take courses on interdisciplinary work and provide each other micro-trainings on enabling technologies. Leaders of the Cluster Research Domains and the work streams get special training on leading an interdisciplinary group. But also the promotion of young talents is important to sensitize students for the challenges and chances of interdisciplinary research. Therefore, Research-Oriented Teaching is performed by adding research topics into lectures, supervising interdisciplinary theses, and integrating student assistants into cluster-related tasks.

1.5 Conclusion

Production technology is a key part of our economy and needs to adapt to changing societal needs. Hence, more knowledge about processes and the interaction between humans and the processes have to be gained with available, but unstructured, data. Therefore, the vision of the Internet of Production was introduced, which demands cross-domain collaboration for gaining problem-specific knowledge from adequate and context-aware data. Concepts like the Digital Shadows and the World Wide Lab were introduced, which are based on an overarching infrastructure and bring together the main research domains in production: development, production, and usage. A strong collaboration between researchers from production technology, materials science, information technology, social sciences, and management is mandatory. The domain-driven research challenges lead to new interdisciplinary opportunities. First, success stories and the framework for working interdisciplinary by enabling the researchers through special training are presented.

The Cluster of Excellence Internet of Production reached the middle of the funding phase of 7 years. It can be seen that there is a good progress on reaching domain-specific knowledge through the usage of data-driven methods in the production environment. Although there are already a lot of collaborations between the different disciplines, the different domains have to come closer together. More transferable methods need to be found. With the great challenges ahead – decarbonization of the industry, circular economy, shortage of skilled workers, and aging society – important production and product knowledge must be enhanced and preserved. Therefore, the vision of the Internet of Production must be carried into industry.

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Part II

IoP - Infrastructure

2 Digital Shadows: Infrastructuring the Internet of Production

Wil van der Aalst, Matthias Jarke, István Koren, and Christoph Quix

Contents

Abstract

Digitization in the field of production is fragmented in very different domains, ranging from materials to production technology to process and business models. Each domain comes with specialized knowledge, often incorporated into mathematical models. This heterogeneity makes it hard to naively exploit advances

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in data-driven machine learning that could facilitate situation adaptation and experience transfer. Innovative combinations of model-driven and data-driven solutions must be invented but also made comparable and interoperable to avoid ending up in information silos. In future *World Wide Labs (WWLs)*, experiences can be shared, aggregated, and used for innovation. WWLs will be complex, evolving socio-technical networks of interconnected devices, software, data stores, and humans as users and contributors of expert knowledge and feedback. Integrating a large number of research labs, engineering, and production sites requires a capable cross-domain Internet of Production (IoP) infrastructure. The IoP project claims *Digital Shadows (DSs)* to offer a shared conceptual foundation for infrastructuring the IoP. In engineering, DSs were introduced as the data provision link to Digital Twins, whereas in computer science, DSs generalize the well-established concept of database views. In this chapter, we elaborate on the roles of DSs in infrastructuring the IoP from three perspectives: analytic functionality, conceptual organization, and technical networking. As an example where an integrative DS-like approach is already highly successful, we showcase the approach and infrastructure of the process mining field.

Keywords

Digital twin · Digital shadow · Data integration · Industry 4.0 · Internet of production · Manufacturing · Industrial infrastructure · Process mining

2.1 Introduction

Manufacturers need to handle vast volumes of heterogeneous, raw data with some machines capable of generating more than 1,000 different sensor signals, partly with enormously high sampling rates. Such amounts of data cannot be processed together close to their sources anymore. In addition, production processes may involve multiple machines, storage systems, transportation systems, and interactions with suppliers and logistic partners. Along industrial process chains, this complexity increases due to the different processes and, in some cases, within a single production line for reasons of variant diversity and mass customization.

Today, data is often stored without conceptual descriptions, engineering models, and their relationships, which prevents systematic reuse within and particularly across domains such as materials engineering, production technology engineering, operations, and management, as well as inter-organizational information exchange. The *Internet of Production (IoP)* project at RWTH Aachen University aims to investigate, prototypically demonstrate, and evaluate worldwide networks of production sites and research labs to cope with the challenges of industry like productivity, product variety due to make-to-order manufacturing, and sustainability. In our vision, a global interconnection of production sites and research labs forms the World Wide Lab (WWL), offering a controlled exchange of Digital Shadows even across organizational boundaries.

Compared to strategies like "Industry 4.0," "Industrial Internet of Things," and "Made in China 2025," the IoP aims to go deeper in its cross-domain focus. It requires novel domain-specific combinations of physical models and data-driven machine learning algorithms but also a common abstraction that makes them interoperable and exchangeable. The IoP project postulates the so-called Digital Shadows to be suitable for this task. As a situated (often real-time) means of reducing the statistical uncertainty of even the most advanced generic mathematical engineering models, DSs require the continuous integration of underlying data sources, which are heterogeneous in location, structure, and semantics, toward purpose-driven, aggregated, multi-perspective, and persistent datasets (Becker et al., 2021). The resulting datasets can feed and/or trace simulation models in Digital Twins. Our core hypothesis is that a well-designed collection of DSs is suitable as a cornerstone of infrastructures for designing, creating, and managing WWLs. This requires not only the powerful functionalities enabled by the novel construction of DS but also a suitable conceptual organization and physical infrastructure design.

According to theories of digital infrastructures (Pipek and Wulf, 2009), their successful creation and evolution require an iterative process of top-down design and bottom-up usage feedback, called infrastructuring. The IoP infrastructuring process, therefore, drives the further DS formalization and tooling with a stepwise buildup of more and more complex use cases, starting with local domain-specific and first data exchange experiments and prototypes, followed by more and more complex scenarios in WWLs among scientific and industrial partners.

This chapter is organized as follows. After reviewing recent related work in the fields of Digital Twins, Digital Shadows, and sovereign cross-organizational data sharing in Sect. 2.2, this chapter, therefore, discusses challenges for the functional requirements, conceptual modeling, and technical infrastructure of a DS-based IoP infrastructure in Sect. 2.3.

Complementing the already well-understood logic-based foundations and algorithms for heterogeneous data integration and analytics around structural data models (Jarke and Quix, 2017; Lenzerini, 2019), the DS-like formalisms of process mining constitute a highly successful core middle-ground abstraction for dynamics in the IoP, which we summarize in Sect. 2.4. Section 2.5 concludes the chapter.

2.2 Related Work on Digital Twins and Digital Shadows

Digital Twins have become a hot topic in the engineering literature in the last years, and several surveys have appeared. The DT concept was initially proposed by Grieves as a vision toward product life cycle management (Grieves, 2014). Their fundamental structure consists of a physical system and a corresponding computational model serving as its DT, which are dynamically synchronized through a mechanism known as *twinning*, cf. Fig. 2.1. The DT is generally regarded as a structural, optimization, or simulation model that represents the physical system. The twinning process involves two phases: the physical-to-virtual link, where physical system measurements are analyzed and the DT is modified accordingly, and the virtual-to-physical link, where the physical system is controlled using the information obtained from the DT.

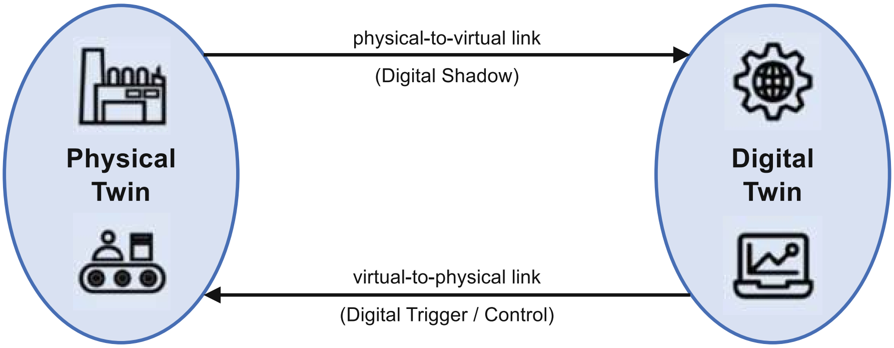

Fig. 2.1 Digital Twinning concept iterating between physical and Digital Twins (© the authors)

One significant development that has been consistently pursued in the context of the IoP is the recursive extension of the concept of a "physical system" to include cyber-physical (production) systems (CP(P)S). This extension involves managing federated networks of DT pairs within and across multiple interacting life cycles of engineering, production, and product usage. Lim et al. (2020) identify eight different perspectives and provide an in-depth analysis of engineering product life cycle management and business innovation. Meanwhile, Zhang et al. (2019) and Melesse et al. (2020) argue that research on DTs for product-service systems is becoming increasingly important due to the significant value that services can provide.

Fuller et al. (2020) identify Digital Shadows with the physical-to-virtual link, as shown in Fig. 2.1. However, the reality of this link is much more complex.

In their extensive review of the literature, Jones et al. (2020) divide the physical-to-virtual link into two parts: a *metrology* component that involves specifying and executing necessary measurements for real-time data analytics and a *realization* component that determines the changes required in the DT. Consistent with our findings in Pennekamp et al. (2019), they also highlight the IT requirements for implementing the link. These include advanced network algorithms based on Industrial IoT frameworks, such as those used for sensor and actuator management; efficient and effective information logistics over these networks; and data management, monitoring, and learning algorithms necessary for each step.

Bauernhansl et al. (2018) suggest a roadmap for examining the intricate information logistics that are necessary for DSs to efficiently and effectively provide information in today's dynamic industrial environment. Although a few studies have acknowledged the IoP's emphasis on the extensive integration of rapid mathematical engineering models and advanced data-to-knowledge pipelines using layers and networks of DSs as reusable objects, we are not aware of any studies that have investigated this topic in comparable depth and breadth.

Bazaz et al. (2020) highlight how the absence of clear data ownership can exacerbate these challenges. Moreover, a significant concern, especially by highly specialized production enterprises, is the loss of sovereignty over the use of their confidential know-how in such information logistics settings by keystone-player-driven data platforms or the violation of data privacy laws. To address these problems, the concepts of Industrial Data Spaces and alliance-driven platforms have been derived in broad empirical studies (Otto and Jarke, 2019) and elaborated into a comprehensive reference architecture (Otto et al., 2022) for alliance-driven data exchange ecosystems. The IoP infrastructure adopts this basic sharing approach but makes it more specific by choosing Digital Shadows as the unit of knowledge sharing in inter-organizational data exchange. The arguments for this choice include, from a business perspective, the added value created by advanced methods for producing the Digital Shadow and the provenance documentation associated with that. From a technical perspective, the relatively small size of DSs compared to the vast amount of underlying data reduces network contention and enables the distribution of computations over multiple levels of Digital Shadows.

2.3 Infrastructure Requirements and DS Perspectives

The IoP infrastructure for data processing, AI, networking, and smart human interfaces needs to integrate methodologies from different perspectives, as summarized in Fig. 2.2. The requirements for the *functional perspective* include a range of powerful techniques for a huge variety of short-, medium-, and long-term tasks but also for task layers all the way from basic data integration up to model-integrated AI shadows and suitable interactive visualizations. In designing all these, there should be a balance between general and still directly applicable data science and ML techniques, keeping the continued shortage of human specialists in mind.

For the *conceptual foundation* linking these many aspects of DS, data must have semantics but at the same time be generic. Much of the existing modeling work in this area is either too general that one cannot apply interesting data science/ML techniques or it is very specific for a particular application.

Distributed execution and controlled sharing of data analysis functions with high performance, reliability, and security is addressed from a *physical perspective*. This perspective aims to provide an interconnected technical backbone of the Internet of Production, as sketched in the lower layer of Fig. 2.2.

The following subsections elaborate on these challenges in some more detail.

2.3.1 Functional Perspective: Data-to-Knowledge Pipelines Using Domain-Specific Digital Shadows

Digital Shadows provide domain-specific access to heterogeneous data from different sources, structures, and semantics. They prepare the application of data-driven machine learning methods, embedding engineering knowledge in the form of physical, predictive, and simulation models to raise relevance, performance, and explainability. For example, reduced mathematical models can be exploited as evaluation functions in neural network-based learning; conversely, the statistical uncertainty handling of generic mathematical models can be made significantly simpler and more precise by continuous monitoring of actual situations. Generally speaking, this requires deep and broad extensions to the emerging field called informed machine learning, as surveyed by von Rueden et al. (2021).

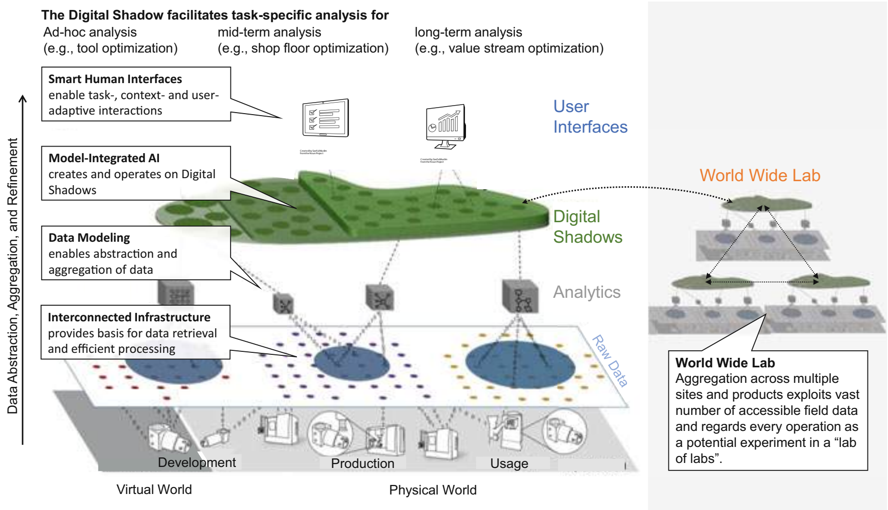

Fig. 2.2 Interconnected infrastructure for Digital Shadows in the Internet of Production (Brauner et al., 2022) (© the authors)

The data-to-knowledge pipelines (pathways from lower to higher levels in Fig. 2.2) help to transform massive data into insights while providing meaningful actionable knowledge to decision-makers.

Today, the transferability of learning outcomes between fields of application has only been realized in a few particular contexts. Correspondingly, the network of production-specific data-to-knowledge pipelines could enable the derivation of similarities between pipelines across different production settings to enable transfer learning within and across domain or organizational boundaries. As one example, the IoP project developed a user-centered planning tool with an integrated decision support system based on human-centered AI (Schemmer et al., 2020) that demonstrates how to increase the efficiency and reproducibility of planning process chains for fiber-reinforced plastics production.

Due to the massive sensor stream processing and real-time analytics in the IoP, data cleaning and integration may only happen on demand. The current numerical design of manufacturing processes based on Digital Twin simulations is unsuitable to directly support real-time decision-making at the machine. The Digital Shadow is based on a reduced simulation model, which focuses on only currently relevant aspects. This data must therefore be adequately provided and composed.

Since this data-driven approach blurs the distinction between design time and runtime of production systems, novel validation techniques need to be developed to account for and monitor adaptations in functionality, contexts, and constraints. Using AI methods allows distributed planning and scheduling as well as execution of production processes at all levels. Novel visualization and interaction methods need to be developed that minimize biased decision-making and support the understanding of complex data. Process mining can be used to diagnose and improve quality and performance problems in complex systems with high concurrency.

2.3.2 Conceptual Perspective: Organizing DS Collections in a WWL

Although the infrastructure for the IoP should be *generic*, Digital Shadows need to be contextualized using purpose-oriented metamodels and ontologies. Data-driven approaches (e.g., machine learning, visual analytics, heterogeneous data integration, or process mining) require data and models in particular formats. On the one hand, aspects such as latency, scalability, connectivity, and security can be largely addressed while abstracting from the semantics of data and models. On the other hand, data can only be used in a meaningful way if there are suitable metamodels and/or ontologies. Models also need a specific structure and semantics in order to be used in an expressive manner.

For example, one can view both Petri nets and neural networks as graphs. However, this is not very meaningful. Analysis techniques for both classes of models are disjoint. Hence, data and models need to have structure and semantics to be meaningful in the context of the IoP. However, one should also avoid building an infrastructure and using data formats and models that are specific for a particular application (e.g., data generated by a particular machine). Different applications should use the same IoP infrastructure, and data formats and models should be reusable. One does not want to create new storage formats or machine learning techniques when a new machine is added. In other words, we need to find a trade-off between keeping things as generic as possible and at the same time being specific enough to create standardized storage formats and model types that enable the creation of data-driven techniques that help in decision-making and process improvement.

It is essential that the huge amount of data is organized and contextualized according to metamodels. The metamodels must be integrated into a cross-disciplinary life cycle with iterative data aggregation along sequential engineering stages. This requires concepts on storing and linking data from distributed stores within the Digital Shadow.

Specifically, partial metamodels are being investigated from the following perspectives:

- The bottom-to-top pipeline in Fig. 2.2 derives a hierarchy of DSs using principles of database view management in heterogeneous data integration and mining (Liebenberg and Jarke, 2020).
- From a software engineering and research data management perspective, DSs are software artifacts created by model-driven generation and documented according to FAIR principles with full relevant provenance and context information (Becker et al., 2021).
- From an analytics and specifically process mining perspective, data must be interpreted and integrated under an event-centric metamodel, cf. Sect. 2.4.

- From a cross-organizational sharing perspective, DSs are valuable and therefore threatened exchange objects for which a metamodel must allow the representation and monitoring of suitable service-oriented policies and business models (Jarke, 2020).
- A metamodel of the physical infrastructure underlies the secure and reconfigurable workflows of efficient, safe, and secure distributed computation, storage, and transport in complex physical networks (cf. Sect. 2.3.3).

Following established practice in metamodeling for method engineering (Jeusfeld et al., 2010), each of these perspectives needs individual "middle-ground" abstractions in the form of dedicated reference metamodels (see example in Sect. 2.4) whose inter-relationships can be maintained by their linkage to a generic meta-metamodel of DSs with shared domain terms. Such a well-organized collection of interrelated metamodels is under iterative development in the IoP cluster, reflecting ongoing experiences with many specific use cases within and beyond the cluster.

2.3.3 Physical Perspective: Interconnected Technical Infrastructure

The envisioned Internet of Production infrastructure ranges from monitoring and control information at the shop level to process development and analysis. Achieving this requires a combination of network infrastructure measures and scalable data stream processing techniques, along with decentralized process control methods, to enable high-performance, reliable, safe, and secure distributed communication networks that support distributed multi-agent model executions and data flows. A dynamically reconfigurable architecture for these production-specific data flows then enables secure industrial cooperation, which in turn leads to a steep increase in data produced and consumed.

The requirements of the technical infrastructure can be grouped according to three core challenges: *Seamless low latency* enables adaptive control operations within network infrastructures. *High-performance* adaptive stream processing components provide scalability. *Security* is key in industrial cooperation scenarios through data security, data sovereignty, and stakeholder confidentiality.

The specific trait of these challenges is a trade-off, depending on whether data is in motion, in use, or at rest. For example, for scalable data processing, data are moved across a network to a cloud environment, thereby improving performance while increasing latency and possibly decreasing security. Data in use resides in non-volatile media where it can be processed with low latency. Data at rest, stored in data warehouses or data lakes, enables long-term observation and analysis.

Starting with near-to-machine edge processing, the technical infrastructure continues with processing rules that can be efficiently implemented in hardware in a WWL. For example, an early IoP demonstrator (Pennekamp et al., 2020) demonstrates executing performance comparisons among companies in the injection molding industry under encryption, i.e., without revealing companies' sensitive data to anyone. The approach utilizes homomorphic encryption to protect sensitive information when performing computations on joint data.

2.3.4 Toward an Empirically Grounded IoP Infrastructure

A core goal of the IoP project is to find an overall architectural approach that brings these perspectives together. Toward this purpose, numerous individual use cases and experiments are conducted concerning different domains and perspectives of DS development and usage, as reported in the remaining chapters of this book.

A series of increasingly powerful partial operational infrastructures are needed to do this. On the one hand, they must allow researchers to demonstrate and evaluate the DS-based approach of the cluster from engineering, social, economic, and IT perspectives. However, on the other hand, they must interoperate with commercially used tools to enable cooperation with existing lab equipment and industrial environments. AI-inspired multi-agent architectures have been studied in Liebenberg (2021) as a promising approach to bring several of the mentioned DS perspectives together. It partially automates the search for data, knowledge, and Digital Shadows and demonstrates that a combination of social and technical agents is feasible in a WWL yet requires semantic interoperability to achieve the needed provenance and explainability.

The infrastructuring approach maps formal strategic dependency and goal models down to software agents executed in a Kubernetes infrastructure that is in turn linking diverse professional data management systems (loosely integrated as a data lake) and newly developed microservices. The technical IT infrastructure was built on an open-source software stack ensuring interoperability to commercial tools such as Azure and MindSphere. Technically, this lays the foundation for automated data streaming of sensor data from machines to their analysis by dynamically providing connectivity, storage, and computing resources. The embedded data lake permits the handling of relational, graph-based, document-oriented, and time-series data.

To illustrate the combination of IoP-specific and existing commercial resp. open-source technologies in this multi-agent architecture, we briefly sketch its application in a quite demanding engineering use case.

The high-pressure die casting process is a highly automated production technology that generates large amounts of data. Yet, the extensive breadth (number of values) and depth (frequency and precision) require domain knowledge of the process to select required data to facilitate product quality and productivity improvements. In an experimental setup, Rudack et al. (2022) and Chakrabarti et al. (2021) accessed multiple data sources based on the Open Platform Communication Unified Architecture (OPC-UA) and transmitted them to a streaming pipeline defined in the low-code programming environment Node-RED and executed by Apache Kafka. The data are subsequently stored in our data lake, utilizing a MinIO object store as the underlying storage system. A systematic hierarchy of high-dimensional DSs for data analytics is combined with an AI-based recommender system for interactive visual analytics, e.g., in product quality assurance (Chakrabarti et al., 2021).

Tests confirm decent analytics capabilities and interactive usability at the functional level, which deeper semantic models of the process will further improve. They also show an industrially relevant performance for the use case, which requires up to a few hundred messages per second.

2.4 Example of a Successful DS-Based Metamodel: Process Mining

As stated before, for the most relevant perspectives on the IoP, we need to find trade-offs between keeping things as generic as possible and being specific enough to create standardized storage formats and model types that enable the creation of data-driven techniques that help in decision-making and process improvement. In this section, we use *process mining* as an example technology that illustrates such a trade-off nicely. Process mining is generic and not tailored toward specific processes but provides a range of supporting techniques and tools. Moreover, process mining is well-suited to analyze and improve production processes. For example, most car manufacturers (e.g., BMW, Volkswagen, Ford, Toyota, Skoda, Fiat, Porsche, and Ferrari) already use process mining, e.g., to ensure the timely delivery of parts from suppliers, to optimize painting and assembly processes, to distribute cars, and to improve maintenance. In the context of IoP, we analyzed, for example, the production of e.GO cars at the plant in Aachen.

The starting point for process mining is *event data*. An event refers to an *activity* happening at a particular point in *time*. In a classical event log, each event refers to precisely one *case*. An event may have many more attributes (e.g., cost, resource, location, and organizational unit). However, the attributes activity, timestamp, and case are mandatory. Process mining aims to improve operational processes by systematically using such event data (van der Aalst, 2016). Process mining techniques utilize a combination of event data and process models to gain insights, identify bottlenecks and deviations, anticipate and diagnose performance and compliance issues, and facilitate the automation or elimination of repetitive tasks (van der Aalst and Carmona, 2022). The process mining discipline focuses on concrete tasks such as process discovery (turning event data into process models (van der Aalst, 2016)) and conformance checking (diagnosing differences between modeled and observed behavior (van der Aalst, 2016; Carmona et al., 2018)).

There are several open-source process mining tools; the best-known are ProM, PM4Py, RapidProM, and BupaR. There are also over 40 commercial process mining tools (see processmining.org for an overview). It is estimated that already over half of the Fortune 500 are applying process mining (Reinkemeyer, 2020). Examples include Deutsche Bahn, Lufthansa, Airbus, ABB, Siemens, Bosch, AkzoNobel, Bayer, Neste, Pfizer, AstraZeneca, MediaMarkt, Zalando, Uniper, Chevron, Shell, BP, Dell, Nokia, and the car manufacturers mentioned before.

There is a growing consensus that the assumption that each event refers to precisely one case is limiting. This is particularly relevant when analyzing production processes. One assembly step may involve different parts, a machine, and an operator. This leads to the well-known convergence and divergence problems (van der Aalst and Berti, 2020; van der Aalst, 2021a). The *convergence problem* surfaces when a fine-grained case notion is used and the flattening of the event data leads to the unintentional replication of events, e.g., an assembly step is replicated for all the parts involved in it. The *divergence problem* appears when a course-grained case notion is used and causal relations between events get lost. Classical process mining forces the adoption of a single view of the processes under consideration. *Object-centric process mining (OCPM)* addresses the limitation by allowing for any number of objects per event (van der Aalst and Berti, 2020; van der Aalst, 2021a). This extension is highly relevant for the IoP and its Digital Shadows. Examples of objects are products, sub-assemblies, parts, robots, workers, machines, conveyor belts, etc. Events correspond to transformation, transportation, and assembly steps. In IoP, we analyzed assembly processes using real-world data from Heidelberger Druckmaschinen AG, a global manufacturer of printing presses. Heidelberger's printing presses are composed of many different parts, making the traditional case notion limiting. Therefore, we combined object-centric process mining where objects are organized in bills-of-material (Brockhoff et al., 2022).

OCPM uses the *metamodel* shown in Fig. 2.3. The metamodel is generic but specific enough to allow for analysis, discovery, conformance checking, decision-making, and automated process improvements. As mentioned earlier, the IoP strongly relies on data that have clear semantics and that allow for a range of

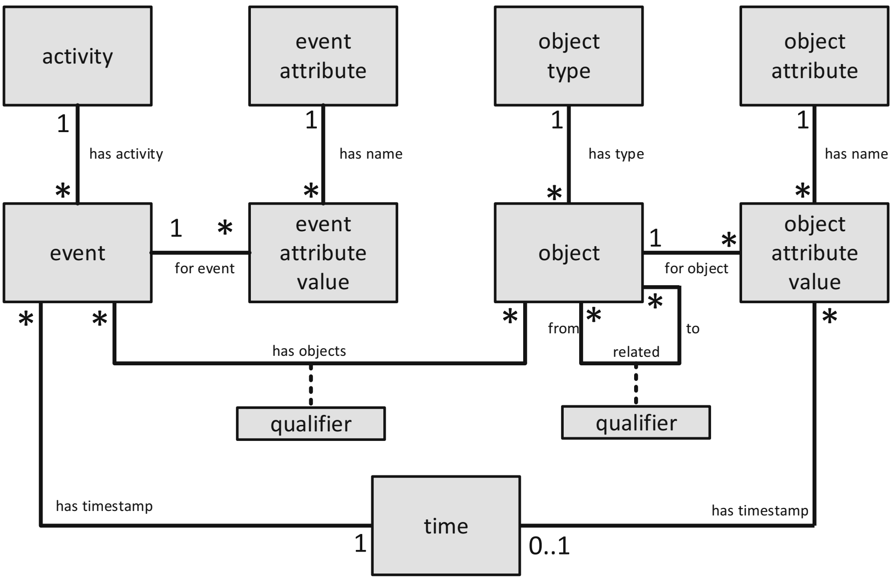

Fig. 2.3 Process mining metamodel: events have a timestamp, an activity, and other event attributes. An event may refer to any number of objects. Each object has a type and attributes that may change over time

techniques, without being application-specific. The two main ingredients of the metamodel shown in Fig. 2.3 are *events* and *objects*. An event has one activity and a timestamp. In addition, an event may have additional attributes such as costs, energy, coordinates, etc., and an event may refer to any number of objects. Each object has a type and may have any number of additional attributes. The values of object attributes may change over time. Therefore, object attribute values may have a timestamp. Object attribute values without timestamps can be seen as immutable. Object attribute values with timestamps can be seen as updates ordered in time. Objects may refer to other objects using a qualified relationship. For example, it is possible to state that one object is part of another object. There is a many-to-many relationship between events and objects. Also, this relationship is qualified. One may say that an event uses a set of objects or creates a set of objects. Note that when using traditional process mining, there is just one type of objects (called cases) and each event refers to precisely one such object. As mentioned, in IoP, we would like to consider many different types of objects concurrently, including machines, workers, orders, end-products, parts, organizational units, locations, shipments, suppliers, etc.

Figure 2.3 shows an example of a concrete metamodel giving meaning to events, objects, relationships, and attributes. The *object-centric event log (OCEL)* standard provides a storage and exchange format for such object-centric event data (Ghahfarokhi et al., 2021). Note that OCEL makes a few simplifying assumptions, e.g., attribute values cannot change and relationships are not qualified. However, both OCEL and Fig. 2.3 agree on the core concepts. Using such object-centric event data, it is possible to discover object-centric process models and check conformance automatically (van der Aalst and Berti, 2020; van der Aalst, 2021a). For example, van der Aalst and Berti (2020) shows that it is possible to automatically learn object-centric Petri nets showing frequencies, delay distributions, and probabilities in an integrated process model describing the interactions between any number of object types. Next to process discovery and conformance checking, there exist techniques to predict the behavior of object-centric processes, detect concept drift, analyze performance, and recommend actions to reduce operational friction.

By selecting a set of object types and a set of activities, one can easily create views on the whole. For example, one can focus on particular machines, products, and phases of the production process. For each view, it is possible to automatically create process models showing performance and compliance problems.

Such views are composed of object-centric event data projected onto selected object types and activities and object-centric process models. These provide concrete Digital Shadows that can be used to manage and improve production processes. The metamodel shown in Fig. 2.3 strikes a balance between generality and specificity. Application- or domain-specific data need to be mapped onto generic concepts such as events and objects, thus allowing for a range of techniques implemented in existing process mining tools.

Figure 2.4 shows the process mining pipeline (van der Aalst, 2021a). The first step is to extract *object-centric event data* from existing data sources (e.g., ERP and CRM systems). Such data can be *preprocessed*, e.g., selecting activities and object

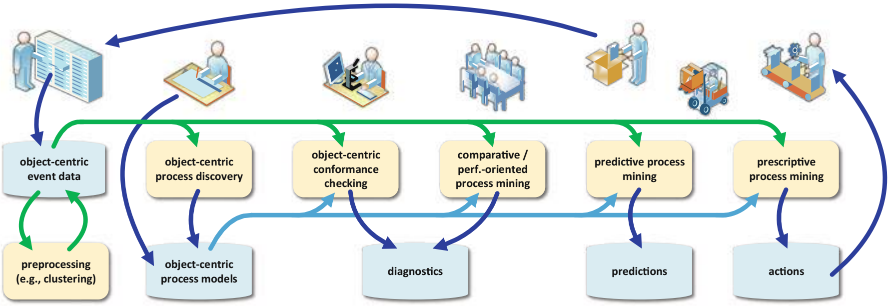

Fig. 2.4 The process mining pipeline showing the different types of artifacts and data processing steps starting from object-centric event data

types, or using automated clustering. For the resulting views, dedicated object-centric process models can be derived, thus forming Digital Shadows. Object-centric *process discovery* techniques can derive object-centric Petri nets, Business Process Model and Notation (BPMN), and Directly-Follows Graph (DFG) models without any modeling.

Given the object-centric event data and object-centric process models, one can apply object-centric *conformance checking* to find and diagnose deviations. Similarly, one can apply *comparative and performance-oriented process mining* techniques to diagnose execution gaps, i.e., significant differences between best practices and actual process executions (van der Aalst et al., 2021).

In IoP, we develop open-source software tools such as OCPM (www.ocpm.info) and OCPI (www.ocpi.ai) to support object-centric process mining using OCEL (Ghahfarokhi et al., 2021). However, our ideas have also been implemented in commercial software systems. A notable example is ProcessSphere by Celonis. This helps us to realize a World Wide Lab leveraging event data from different organizations. Process mining techniques can provide *backward-looking* or *forward-looking* analysis. Backward-looking analysis involves identifying the root causes of bottlenecks in production processes, while forward-looking analysis involves predicting the remaining processing time of ongoing cases and recommending actions to reduce failure rates. Both types of analysis can lead to actionable insights, such as implementing countermeasures to address performance or compliance issues (van der Aalst and Carmona, 2022). Figure 2.4 shows *predictive process mining* as an example of a forward-looking form of process mining. This results in predictions that can be used proactively. The final step in the pipeline depicted in Fig. 2.4 is *prescriptive process mining*. In this step, event data, process models, and objectives are combined to trigger actions addressing observed or predicted performance and compliance problems.

One main challenge is to extract event data from the source systems. Event data may exist at different levels of granularity, and often there are data quality problems. Once the data is extracted, cleaned, and stored using the metamodel in Fig. 2.3, the whole pipeline depicted in Fig. 2.4 can be applied.

Another major challenge is the collection of event data across organizational boundaries. Sharing event data may not be possible for some organizations, and they may use unique identifiers and logging practices (van der Aalst, 2021b). *Federated process mining* aims to tackle these problems by creating cross-organizational event data in such a way that confidentiality is ensured (van der Aalst, 2021b). Federated event logs make it possible to compare processes in different organizations and to analyze processes spanning multiple organizations.

Process mining techniques benefit directly from a technical infrastructure that is scalable, reliable, and safe. Process mining provides a strong conceptual foundation for realizing Digital Shadows and a World Wide Lab. The metamodel in Fig. 2.3 shows that it is possible to provide generic technologies close to production processes. The wealth of process mining tools and techniques supports the functional perspective of the IoP infrastructure.

Although the scope of process mining is broad and covers all optional processes, it is just one building block of the bigger IoP infrastructure. For example, techniques for process mining do not support continuous processes and unstructured data (e.g., computer vision and object recognition).

2.5 Conclusion

The infrastructure of the Internet of Production (IoP) research cluster aims, in the long term, to significantly facilitate the design, operation, and usage of World Wide Labs for more effective, scalable, safe, and secure data and knowledge sharing and usage across boundaries of domain, organizations, and even cultures. To bridge these boundaries, this chapter presented Digital Shadows as a core metaphor across all perspectives of the IoP infrastructure.

We showed that DSs have many different facets and roles, each of them requiring specific theoretical foundations, such as supporting (meta)models, algorithms, and software tools. For some facets, such as process mining or heterogeneous data integration, existing foundations just need to be adapted to some special requirements of the production sector; for others, we still need to identify such "middle-ground abstractions" that make overly abstract meta-metamodels more usable while still providing practical improvements for individual use cases and customer applications.

These theoretical developments are empirically confronted with a large number of interdisciplinary IoP use cases across research labs and with practice partners. To enable these use cases, a series of increasingly powerful experimental infrastructures, including linkage to widely used existing systems, are being developed.

While the present chapter reviewed the overall vision, challenges, and an integrative DS example as an infrastructuring concept, the status achieved in the first three project years is presented in the following three chapters of this book, addressing technical details, initial research results, and use cases for the physical, conceptual, and functional-algorithmic perspectives.

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Evolving the Digital Industrial Infrastructure for Production: Steps Taken and the Road Ahead

3

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Abstract

The Internet of Production (IoP) leverages concepts such as digital shadows, data lakes, and a World Wide Lab (WWL) to advance today's production. Consequently, it requires a technical infrastructure that can support the agile deployment of these concepts and corresponding high-level applications, which, e.g., demand the processing of massive data in motion and at rest. As such, key research aspects are the support for low-latency control loops, concepts on scalable data stream processing, deployable information security, and semantically rich and efficient long-term storage. In particular, such an infrastructure cannot continue to be limited to machines and sensors, but additionally needs to encompass networked environments: production cells, edge computing, and location-independent cloud infrastructures. Finally, in light of the envisioned WWL, i.e., the interconnection of production sites, the technical

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infrastructure must be advanced to support secure and privacy-preserving industrial collaboration. To evolve today's production sites and lay the infrastructural foundation for the IoP, we identify five broad streams of research: (1) adapting data and stream processing to heterogeneous data from distributed sources, (2) ensuring data interoperability between systems and production sites, (3) exchanging and sharing data with different stakeholders, (4) network security approaches addressing the risks of increasing interconnectivity, and (5) security architectures to enable secure and privacy-preserving industrial collaboration. With our research, we evolve the underlying infrastructure from isolated, sparsely networked production sites toward an architecture that supports high-level applications and sophisticated digital shadows while facilitating the transition toward a WWL.

3.1 Introduction

With the deep integration of distributed, heterogeneous data producers and the incorporation of intelligent, reactive consumers that reliably exchange and evaluate data and make decisions in real time, the Internet of Production (IoP) is changing the requirements for the underlying physical information infrastructure. Concepts, such as digital shadows, data lakes of production, and the World Wide Lab (WWL) with its global knowledge exchange (Brauner et al. 2022), require a foundation that enables the seamless execution and transfer of physical, simulated, and data-driven production models and data streams with excessive peak loads in real time (Pennekamp et al. 2019a). The weakened boundaries between data processing and network communication and the gradual shift of computational tasks closer to the machines form the basis for the integration of complex, high-quality control with maximum flexibility into a decentralized infrastructure to enable the offloading of data-intensive tasks (Chang et al. 2014). Dynamic reconfigurability of the underlying architecture guarantees constant adaptation of the processes to the needs of production technology. Since a significant part of the value creation of the IoP is generated by the exchange of information between stakeholders from different, possibly mutually distrusting cooperation partners, an infrastructure must take confidentiality into account (Gelhaar et al. 2021). Despite extensive digitization, networking, and autonomy of production sites, humans also remain an important factor in the operation, maintenance, and optimization of plants, systems, and processes, as well as in decisions derived from an exchange of information (Neumann et al. 2021).

An underlying technical infrastructure that meets these requirements has to include all components of production sites, ranging from sensors and actuators that are integrated into production machines to distributed data centers in the cloud, as shown in Fig. 3.1. Digital shadows are a core concept of the IoP (Brauner et al. 2022) and correspond to representations of data that need to be handled within the infrastructure throughout all common states of data, i.e., at rest, in motion, and in use. Addressing the needs of the proposed WWL, the infrastructure further needs to be

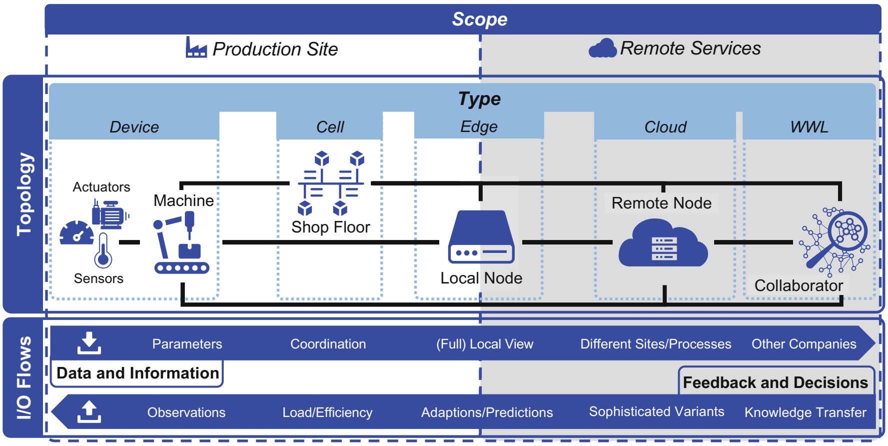

Fig. 3.1 The digital industrial *Infrastructure of Production* is characterized by a nonlinear topology, individual data and information flows for all nodes, and a scope increasingly reaching from isolated production sites to remote services and beyond company borders to realize a World Wide Lab

able to move data across stakeholders. In the underlying technical infrastructure, any processed data (and information) is thus part of constantly evolving digital shadows as the prevalent tasks of preprocessing, aggregation, filtering, data translation, and data sharing all constitute task- and context-dependent, purpose-driven, aggregated, and persistent representations and transformations of the originally sensed data. Building upon digital shadows that are primarily concerned with data processing and network communication within the technical infrastructure, we further require an infrastructure that is capable of effectively utilizing the information contained in digital shadows for decision-making. In light of this requirement, the infrastructure also needs to evolve the formal modeling of information (cf. ▶ Chap. 4, "A Digital Shadow Reference Model for Worldwide Production Labs"), which subsequently allows for novel, higher-level computational technologies to exploit the benefits of processed and shared digital shadows (cf. ▶ Chap. 5, "Actionable Artificial Intelligence for the Future of Production").

With a specific focus on the underlying, networked infrastructure, we identify several research questions, especially when having real-world deployments in mind:

- How can we design a reliable and scalable *Infrastructure of Production*, i.e., as needed for the IoP with its unique processing and security requirements, that is capable of handling enormous amounts of data (rates) while being able to integrate heterogeneous, distributed models and data streams on time?
- How can we flexibly deploy workloads in such a decentralized network-enabled environment to allow for adaptable and high-performant control decisions?
- Which approaches enable stakeholders to exchange massive and heterogeneous datasets in such environments while considering their confidentiality needs?

To answer these questions, we focus our efforts on five research areas that build the core of an evolved industrial infrastructure. This way, we cover the broadest possible spectrum of hierarchical levels of production (cf. Fig. 3.1), i.e., we contribute comprehensively to addressing these pressing research questions for real-world use.

In this work, we elaborate on (1) methods for the efficient processing of production data in motion and at rest throughout the node topology illustrated in Fig. 3.1. In the context of production, data is recorded by sensors, machines, and devices. It is further forwarded via edge servers to the cloud and to any collaborators within the WWL. At times, it is also processed directly while being networked in the infrastructure. In line with Fig. 3.1, insights gained from the data and decisions made are fed back to the shop floor and machines to decisively influence production processes. Further areas investigate cross-sectional functions required by all hierarchical levels, such as (2) the overarching interoperability of systems, (3) the controlled exchange of data with various stakeholders, (4) the current state of and future improvements for network security, and (5) the enabling of privacy-preserving industrial collaboration. Furthermore, successfully addressing the research questions, i.e., adapting the infrastructure according to the needs of production technology and the IoP, especially with its novel confidentiality and privacy requirements, can only succeed if different disciplines (domain experts) collaborate (Brauner et al. 2022), in particular given the demand for concepts that scale to industry needs. Otherwise, valuable knowledge will remain in stakeholder-specific data silos where production experts cannot access and utilize it, i.e., valuable potentials are lost. Thus, evolving today's industrial landscape, its data processing, and the foundation for collaborations into a digital industrial *Infrastructure of Production* is of utmost importance.

3.2 State of the Art: Challenges for the Infrastructure

Before we describe how we aid the evolution of the infrastructure in Sect. 3.3, we first provide an overview of and derive challenges for the current *Infrastructure of Production* (Sect. 3.2.1). Afterward, we discuss the state of the research areas that can, once being addressed, enable the Internet of Production (IoP) (Sect. 3.2.2).

3.2.1 An Overview of the Infrastructure of Production

Fueled by the IoP, the technical infrastructure underlying industrial production is in a phase of drastic transformation. As shown in Fig. 3.1 (left), traditionally, industrial devices such as machinery and sensors have only been networked *within* one production site. Typically, a *cell* in a production site corresponds to one shop floor (cf. ► Chap. 11, "Model-Based Controlling Approaches for Manufacturing Processes") or modern production concepts, such as lineless mobile assembly systems (cf. Chapter "Resilient Future Assembly Systems Operation in the Context of the Internet of Production"). Devices within one cell have been interconnected within a dedicated process network with no or only severely limited interconnection to other networks (within the same factory or company), let alone the Internet. With the ongoing digitization, companies tend to move data storage and processing from isolated cells to local nodes at the edge of production, potentially combining data from multiple cells and even across different production sites, but still within and in the control of the same company. Thus, industrial deployments typically still confine knowledge in stakeholder-specific data silos due to omnipresent security and privacy concerns. Consequently, any exchange of data and thus collaboration has not been possible by traditional technical infrastructures underlying industrial systems.

Motivated by the manifold benefits promised by the IoP (Pennekamp et al. 2019a), technical infrastructures of production scenarios increasingly shift toward remote services, including cloud computing services, as highlighted in Fig. 3.1 (right). This shift is mainly driven by the desire to realize digital shadows for various processes and tasks in production (cf. ▸ Chap. 4, "A Digital Shadow Reference Model for Worldwide Production Labs") as well as digital shadow-integrated machine learning and artificial intelligence (cf. ▸ Chap. 5, "Actionable Artificial Intelligence for the Future of Production"), demanding access to various kinds of data from multiple sources as well as requiring immense computational and storage resources. To fulfill this demand, storage and processing of various kinds of production data and corresponding digital shadows is increasingly moved outside the sphere of individual production sites, ranging from edge computing (still mostly in control of a single company), over remote nodes in the cloud, to joint processing and storage at and with collaborators in a globally interconnected World Wide Lab (WWL). Moreover, today's deeply rooted confidentiality concerns in industry still prevent the utilization of digital shadows, data lakes, and industrial collaborations as companies and stakeholders understandably call for appropriately secured approaches. Thus, other than previous paradigms without access to sufficient domain expertise, interdisciplinary research on the IoP can directly account for these additional challenges.

To provide a solid foundation on the technical level to realize these functionalities and ultimately capitalize on the various benefits of the *Infrastructure of Production* and the expected impact of digital shadows, different streams of research need to be tackled. More concretely, providing a fundamental technical infrastructure requires further research efforts on (1) adapting data and stream processing to heterogeneous data from distributed sources, (2) ensuring data interoperability between systems and production sites, (3) exchanging and sharing data with different stakeholders, (4) network security approaches addressing the risks of increasing interconnectivity, and (5) cybersecurity architectures to enable secure and privacy-preserving industrial collaboration. Orthogonal to these technical aspects of the infrastructure, human aspects w.r.t. to the people working on and interacting with production processes (cf. ▸ Chap. 22, "Human-Centered Work Design for the Internet of Production") as well as requirements resulting from new business models and relationships in the WWL (cf. ▸ Chap. 23, "Design Elements of a Platform-Based Ecosystem and Industry Applications") need to be considered.

3.2.2 Research Areas for the Infrastructure of Production

Resulting from the identified key challenges for the *Infrastructure of Production*, we now outline five research areas by discussing the corresponding state of the art and associated research questions. Together, these areas make up the center of our envisioned infrastructure. In particular, the *processing of data* and *device interoperability* enable fundamental interactions between the different entities on a device level. *Data security and quality*, as well as *network security*, provide concepts for securing transmitted data and device interactions. Finally, an *infrastructure for industrial collaboration* promises to enable secured interactions on a higher level of abstraction, e.g., across company borders, to enable the exchange of knowledge.

3.2.2.1 Scalable Processing of Data in Motion and at Rest

Data is recorded, transmitted, stored, and processed throughout the whole topology, as illustrated in Fig. 3.2. Conceptually, it is either in motion, in use, or at rest. Data *in motion* refers to data that moves from a source to a destination within a private or public network. Data *in use* is data that is currently being accessed, processed, or updated. When data is persisted on nonvolatile storage, such as (edge) cloud storage or (industrial) data lakes, it is called data *at rest*. In the following, we separately discuss the subareas of data stream management and analysis and the processing of the data at the network edge, in the cloud, and during transmission.

Data Stream Management and Analysis The huge number of devices and sensors in modern industrial manufacturing sites leads to the production of massive amounts of data in the form of continuous unbounded data streams with a high frequency. Data Stream Processor (DSPs) are systems tailored to the management and analysis of data streams and support the efficient querying and implementation of near real-time applications, such as anomaly detection or alerting. However, the data size emitted by sensors and machines is, in many cases, so huge that the transfer to a central system for further processing and analysis would lead to a network overload (Pennekamp et al. 2019a). Hence, for the data stream processing

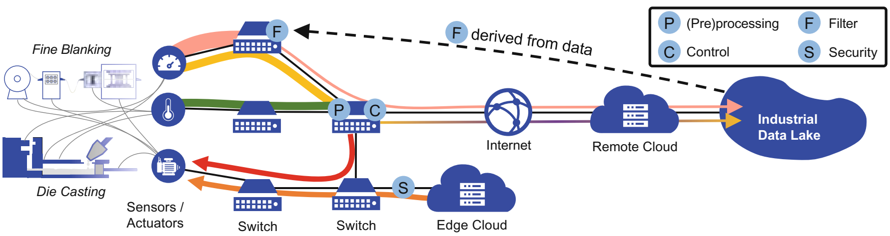

Fig. 3.2 Sensor data is transmitted and processed at various locations throughout the *Infrastructure of Production*. Data streams can already be filtered (F) or (pre)processed (P) in the network. Moreover, they can be protected using secure protocols or gateways (S). Switches can generate control commands (C) significantly closer to the production process than other processing entities

to become horizontally scalable, the workload must be pushed further toward distributed machines, i.e., to the fog and the edge of the network. This approach promises efficient processing where needed while introducing new challenges to DSPs (Zeuch et al. 2020). Here, as illustrated in Fig. 3.2, one fundamental question is where to place the operators, such as filters (F), of the processing graphs maintained by these DSPs.

Furthermore, such a processing infrastructure must also support highly heterogeneous data from various sources, such as sensors, machines, and cameras. Also, when many components and sensors are involved, data quality can be highly variable, as these components may fail or emit invalid data. Hence, data quality needs to be assessed and considered in each step of the infrastructure. Produced data further needs to be enriched with standardized domain-specific and processual metadata, reflecting the context and provenance of the data stream elements. The metadata increases its value for higher-level applications and makes it suitable for data exchange in the IoP. Different levels of data richness hereby represent digital shadows of different granularities, serving the needs of different applications.

Edge Computing An edge device is any type of computational resource that resides between the original data source and cloud-based data centers. Such devices range from very limited industrial components, often with interfaces to industrial control systems, to powerful computing units with special hardware specifications, e.g., additional graphics processing units (Qi and Tao 2019). The goal of edge computing is to transform and reduce data locally by eliminating redundancies as close to the data source as possible with limited resources to provide faster feedback on events in the data or to reduce the data volume load on the network. The IoP presents new challenges for edge computing, as data volume and velocity, the feedback required for control mechanisms, and the complexity of models require a fine-tuned computational hierarchy (Glebke et al. 2019). Data is only available to a limited extent on a local level. Thus, calculations, models, and decisions based on them can only include a slice of the globally available data. The key challenge lies in the use of limited resources and data access to extract information, reduce redundancy, and provide feedback latencies that fulfill use case-specific requirements. For example, when considering the architecture of Fig. 3.2, an edge cloud could perform computations close to the machine to save latency compared to processing in a remote cloud that first mandates a time-consuming transmission of relevant data.

Cloud Computing A big challenge in current manufacturing information systems is the organization of data flows, data collections, and their analysis in a centralized manner, allowing all participants to either ingest, modify, or extract information. To this day, most manufacturing systems use sensor-actuator systems without giving access to outside IT systems (i.e., Operation Technology (OT)-Internet Technology (IT) separation (Garimella 2018)) to allow data analytics and condition monitoring. The usage of manufacturing data across multiple production steps and distributed production sites and along the whole lifecycle holds great potential for saving costs, for a more efficient use of resources, and for an increase in product quality

(Rath et al. 2021). However, a centralized cloud infrastructure that integrates all relevant production data is a very complex system that is difficult to build, maintain, and run, as today's data processing systems are characterized by a fragmentation of computing and storage resources. Reasons for this fragmentation are either missing organizational infrastructures like user management across multiple systems or vendor lock-ins which limit the accessibility of data by the use of proprietary technology. Manufacturing sensors and actuators can produce data up to a few GHz, which typically results in enormous amounts of data. As discussed before, the amount of data produced by a manufacturing system puts large requirements on the networking, processing, and storage infrastructure. These data streams only produce data during their use, i.e., the stream of data is more inconsistent and produces large bursts. Having a flexible and agile infrastructure that continuously adapts to these bursts and also provides an automated way of scheduling and scaling applications inside the data center is a large challenge (Brockmann and Kröger 2021). A central concept in the IoP is the data lake (cf. Fig. 3.2), which represents a repository of all (historical) production data. It is implemented as a scalable distributed system and storage while being controlled centrally through a dedicated control plane.

(In-)Network Capabilities The communication network, over which data is transmitted and streamed, is the central connector of all entities within the IoP as it is used to communicate all nonlocal information. In a traditional sense, the network is seen as a "dumb" connection provider that only delivers data. However, research has already illustrated that data rates needed for industrial production processes can become challenging for traditional network setups (Glebke et al. 2019). Additionally, physical signal propagation latencies can also become an influencing factor as soon as computation and/or storage components move to remote facilities, e.g., in the form of cloud providers or the envisioned centralized data lake. Consequently, the existing network infrastructure represents a potential bottleneck for the IoP.

Fueled by novel network programming concepts, such as SDN and P4, research has once again turned its focus to finding ways to leverage previously unused compute resources within the network. This trend is commonly known as *In-Network Computing (INC)* (Sapio et al. 2017). While the exact scope of INC is not yet clearly defined, especially regarding potential overlap with edge computing and whether INC should only refer to computations directly on networking devices, there is already significant work that studies which compute tasks can be best mapped to networking devices and how (Ports and Nelson 2019). In our example in Fig. 3.2, we could, e.g., place a simple processing function (P), such as aggregation, on a switch to significantly reduce the amount of transmitted data. The main challenges arise from the limited computational complexity supported by such devices as they are designed for high-speed packet processing, but only simple calculations. In addition to the challenge of which calculations should be performed using INC, open questions remain as to how and where functionality should be placed within the network and, more importantly, how the functionality should interact with the existing end-host-focused computation and communication schemes. As of today, a generalized, scalable INC framework that solves all or even most of the mentioned challenges is still missing.

3.2.2.2 Device Interoperability

To enable the automated collection of sensor and measurement data, measuring systems (JCGM 2012) must be integrated into the *Infrastructure of Production*. Due to the wide plethora of distributed and used systems, all having their individual manufacturer- and device-dependent interface, this integration is a nontrivial task and requires manual adaption and integration each time (Bodenbenner et al. 2020). The respective individuality and dependency are essentially expressed in the following three aspects (Montavon et al. 2019): (i) manufacturers choose their favored programming language for implementing the systems logic and the API, (ii) the protocol and format for exchanging data differs from manufacturer to manufacturer and often even from device to device, and (iii) the data and system model, which forms the base of the interface of the system, is usually developed from a physical point of view, instead of a functional one, resulting in very low interoperability. Moreover, due to the trend of coupling the internal sensor logic and the communication interface, highly complex cyber-physical systems are formed, which increase implementation, integration, and maintenance efforts (Thramboulidis and Christoulakis 2016).

To seamlessly integrate measuring systems into the overarching digital industrial infrastructure, maximizing the interoperability of used cyber-physical measuring systems is crucial. Concerning the digital infrastructure, this goal requires solving the aspect of technical and syntactic interoperability (Bodenbenner et al. 2021). Although several interoperable data formats and communication protocols are already in use in industry, an approach is missing that decouples the development of internal sensor logic from the communication interface, i.e., the incorporation of interoperable data formats and communication protocols. Solving that would reduce the effort of integration and maintenance of measuring systems in an industrial infrastructure. The challenges and demands described here are of utmost relevance in modern assembly paradigms, such as lineless mobile assembly (Hüttemann et al. 2019). Consequently, we investigate corresponding use cases in our research.

3.2.2.3 Data Security and Data Quality

Given the sensitive nature of (production) data, decisions and data management plans of stakeholders are frequently driven by concerns about data security to secure their competitive advantages, i.e., companies fear a loss of control or unintentional data leaks (Brauner et al. 2022). As a result, in today's environments, data is mostly retained and encapsulated locally at a company (Gleim et al. 2020), potentially even at a single production site or within a specific production cell. Thus, only a single stakeholder can utilize such data silos, resulting in isolated data across the industry. This situation severely hinders industry-wide process and product improvements.

As data is typically kept locally, companies frequently consider security measures unnecessary and neglect to implement data security and privacy solutions and policies in practice. As a result, companies also tend to favor on-premise computing over cloud computing. However, the expected benefits of (i) increasingly automated decision-making within industry (e.g., using machine learning) and (ii) initiatives (including industrial dataspaces (Geisler et al. 2022)) call for revised data security policies that enable companies to globally utilize all available information.

Especially the real-world impact on production lines mandates suitable approaches that can address the security and safety needs of industry while handling the vast amount of (production) data (Henze 2020). In this context, the development of new concepts for data sovereignty, authenticity, verifiability, and accountability has to be considered. So far, these aspects were mostly out of scope as (i) data was rarely used to manipulate live processes and (ii) data was not shared between stakeholders.

Moreover, when considering the trade-off between privacy and transparency, the reliability of information becomes increasingly important. To allow for an ideal utilization, data should be sensed accurately and in a trustworthy manner (Bader et al. 2021), should be authentic and correct (Pennekamp et al. 2020a), and should be semantically enriched (Gleim et al. 2020). Production data that is available within a semantical framework increases the value of such data for downstream data users by lowering the inefficiencies associated with the data exchange as the domain knowledge among stakeholders generally varies, which results in inefficiencies for both data users and data providers. Thus, through semantic enrichment, a frictionless integration with downstream users is enabled. Consequently, semantically enriched production data is far more valuable than raw data, since it is directly available for efficiency gains (without the need for excessive preprocessing). On a similar note, when proposing novel approaches, legal aspects (e.g., liability questions) must be taken into account. In the past, suitable approaches from computer science were not vetted because production environments were neither digitized nor interconnected.

3.2.2.4 Network Security

Sharing data between stakeholders requires significantly intensified communication between all components and layers. Thus, formerly isolated production networks need to be interconnected with other production networks as well as office networks and the Internet. This development facilitates the risk of eavesdropping attacks on sensitive business information or malicious takeover of production machines. Such attacks can not only lead to monetary loss due to the disclosed business secrets but may even cause production outages or create harm to humans (Brauner et al. 2022). Hence, securing these networks is a key requirement.

Since traditional industrial communication protocols, e.g., Modbus, were designed for communication in isolated environments, their design does not include any security mechanisms (Dahlmanns et al. 2020). Furthermore, especially older embedded industrial devices often lack the computational resources to perform state-of-the-art cryptography operations, which becomes particularly problematic in the face of the upcoming shift toward post-quantum cryptography (Henze 2020). Nevertheless, even today, operators connect industrial devices to the Internet while relying on these insecure traditional protocols (Mirian et al. 2016; Dahlmanns et al. 2022; Nawrocki et al. 2020). Consequently, attackers can access these production devices without restrictions, alter messages, or eavesdrop on exchanged information.

In recent years, traditional protocols were retrofitted with Transport Layer Security (TLS), the state-of-the-art protocol for secure communication on the Web. While these protocol versions provide confidentiality, integrity protection, authentication, and access control, their security *in practice* depends on a regularly updated configuration keeping up with changes in the security landscape, e.g., to account for outdated ciphers or hash functions (Dahlmanns et al. 2022). Hence, operators frequently need to assess and adapt their security configurations accordingly. However, security analyses indicate that 42 % of all TLS-enabled industrial protocol deployments on the Internet, i.e., deployments which are reachable in the IPv4 address space, show security deficits (Dahlmanns et al. 2022). Additionally, although OPC UA, the most promising modern industrial communication protocol, was designed with security in mind, research shows that 92 % of the Internet-reachable OPC UA deployments are configured with security deficits (Dahlmanns et al. 2020).

Besides securing communication, exposing networks to the Internet also requires mechanisms to reliably detect potentially remaining attacks (Henze 2020). However, unique opportunities for detecting advanced attacks in cyber-physical systems such as industrial control systems, e.g., by leveraging semantic or process knowledge, remain typically unused today.

3.2.2.5 Infrastructure for Secure Industrial Collaboration

Primarily due to deeply rooted confidentiality concerns (cf. data security), extensive data sharing between stakeholders has not yet been implemented in industrial practice. Hence, corresponding (secure) information flows, while widely researched, remain mostly untapped so far (Pennekamp et al. 2019b). As a consequence, companies cannot fully benefit from the potential of industrial collaboration. Thus, research has to demonstrate the benefits of industrial collaboration to ease its deployment in production environments through a dedicated infrastructure.

The IoP and the proposed WWL further envision modern, dynamically evolving business relationships to address tomorrow's objectives (costs, quality, sustainability, and others (Pennekamp et al. 2021c)) in production. These short-lived relationships significantly challenge today's established level of trust. Thus, to mitigate these concerns, stakeholders demand (proven) technical security guarantees, which underline a strong protection of their sensitive information at all times. Likewise, as automated adaptations based on external information are envisioned, industrial collaborations can only succeed if they ensure a safe operation of all processes (in terms of both human operators and the environment) (Pennekamp et al. 2019b; Henze 2020), while still yielding added value for participating companies.

When sharing data, companies further expect mechanisms to automatically evaluate any allowed secondary use of their shared data, e.g., using data usage policies (Henze 2020; Henze et al. 2016). Otherwise, their concerns could effectively prevent collaboration in industry. Importantly, these challenges do not only concern stakeholders along supply chains but also across supply chains, e.g., if operators of similar machinery collaborate. Importantly, even direct market competitors could collaborate if they are sufficiently supported through technical building blocks. Yet, solutions are only slowly emerging from the domain of traditional cloud computing.

3.3 Evolving Today's Infrastructure for Future Industry Use

Based on the challenges in Sect. 3.2.2, subsequently, we describe for each research area which solutions we have proposed so far. Additionally, we point out further directions that we will pursue to establish a capable *Infrastructure of Production*.

3.3.1 Scalable Processing of Data in Motion and at Rest

In the area of data processing, we separately elaborate on our contributions and further research directions concerning the different building blocks of data stream management and analysis as well as edge, cloud, and in-network computing.

Data Stream Management and Analysis Industrial environments and production sites require data management infrastructures that can handle massive amounts of data in a short time. To tackle the problem of network overload when sending all data to a central data stream processor, we work toward a scalable infrastructure that can distribute a continuous query over a multi-level topology of edge, fog, and cloud computing nodes. An abstraction for a continuous query is a directed acyclic graph of operators, which execute, e.g., filter or windowing operations on streams. The distribution of operators over the graph of potentially changing network nodes is a challenging optimization problem (Cardellini et al. 2016). Thus, various dimensions need to be weighed, e.g., latency requirements or hardware capabilities.

We are working toward a dynamic, robust, secure, and smart infrastructure for production that is able to include different kinds of dimensions, and we particularly investigate dimensions that are relevant for these industrial settings, such as data economy, privacy, and data quality. To address the issues of hardware heterogeneity, we are developing a lightweight and system-agnostic operator library along well-known stream semantics to also enable higher-level declarative and procedural query languages. Furthermore, also new methods for multi-query optimization must be investigated which fit the envisioned infrastructure, benefiting data economy.

Streaming data produced in manufacturing processes is not only valuable for real-time applications but also needed for historical analyses spanning a longer time period. Hence, the data needs to be persisted in long-term storage solutions, such as data lakes. Additionally, a crucial aspect for the Internet of Production (IoP) is the sharing of data with other stakeholders in the World Wide Lab (WWL) and providing input to digital shadows (Brauner et al. 2022). For the scenarios above, properly annotating the data is paramount to prepare it for sharing and reuse. To that end, we develop a metadata model and management concept that (i) allows for the general annotation of data streams along multiple categories and dimensions of metadata and (ii) considers domain-specific semantics and vocabulary from manufacturing for the annotation. Depending on where the metadata emerges, the corresponding functions also need to be deployed to the different levels of the streaming infrastructure topology. In addition, based on previous work (Geisler et al. 2016), we strive to integrate intelligent data quality assessment and improvement to detect data flaws early in the processing pipeline and also prevent swamping the permanent storage into the infrastructure from the cloud to the edge nodes.

Edge Computing Edge devices provide only limited computing resources that have to be leveraged to reduce the amount of data and condense the information density. Raw digital representations of manufacturing processes are often based on multivariate time series that contain a variety of overlapping physical effects encoded in the signals. To realize the potential of this hidden data, domain experts who understand the process and its effects must prepare the data appropriately and make it available for further analysis. The incorporation of domain knowledge at the edge is crucial, since the sooner the data is preprocessed and labeled in a domain-specific way, the less redundant or irrelevant information needs to be passed on. Note, however, that a purely human-based method of preprocessing for knowledge may neglect important unknown effects (Liewald et al. 2022). Thus, edge-based preprocessing pipelines need to incorporate domain knowledge-based approaches into data-driven approaches to fully leverage the power of edge systems.

The processing of a specific manufacturing process in sheet metal forming utilizing high-frequency sensor systems ranging from 10 kHz to 10 MHz reveals the need for edge computing to reduce the data load (Glebke et al. 2019). In this study, nine sets of time series data represent the collective data load during the manufacturing process, which can be broken down into process phases. Each process phase is characterized by specific physical effects, so that only a small part of the time series is useful to include in the modeling. Leveraging this fact, the amount of data relating to a forming operation can be reduced by up to 70 % if, e.g., only the wear or another specific characteristic is of interest (Niemietz et al. 2020). Further studies show that information in raw sensor time series is often redundant, yet classical feature engineering methods based on domain knowledge only partially work (Niemietz et al. 2022). Similarly, features selected by experts are highly redundant and unsuitable for further compression (Unterberg et al. 2021). However, traditional dimension reduction methods can further considerably reduce the amount of data (Bergs et al. 2020). A domain knowledge-based approach combined with methods that independently learn features of time series data can already yield good monitoring capabilities utilizing only computational edge feasible models (Niemietz et al. 2021).

For sheet metal forming and fine-blanking in particular, the IoP enables dynamic processing of all available information specifically tailored to use case needs. Thus, data can be processed locally and only transmitted to the cloud if needed. Otherwise, sensed data, and valuable information within, is lost as the amount of data quickly surpasses the network capabilities or it violates latency requirements in control and feedback loops. These approaches show that using only computationally feasible models for data reduction at the edge in combination with domain knowledge considerably reduces the amount of data that needs to be transmitted to (cloud-based) data centers. However, a comprehensive framework for data reduction and condensation of industrial processes considering the locality of data, models, and knowledge is still missing, as well as methods for combining knowledge and raw data at the edge.

Cloud Computing Cloud technologies, either provided by commercial cloud providers or custom on-premise systems, offer the possibility of dynamically adapting required resources according to demand. This scalability applies to all areas of the data infrastructure: computing power, memory, networking bandwidth, and storage. In addition, clouds are the ideal medium for creating systems that have a uniform level of abstraction and thus appear as a single infrastructure that is available to technical as well as human producers and consumers of data, regardless of their physical location. In this sense, cloud technologies provide not only the computing resources needed but also provide ways to control and manage these systems through the so-called control plane (Casquero et al. 2019). Therefore, cloud infrastructure reduces the complexity of running applications in a distributed environment and abstracts away implementation details of components (Beyer et al. 2016).

Ideally, a cloud infrastructure also provides a set of additional services that centralize functionalities shared by multiple components, such as user management, condition monitoring, or network security. As part of our research, a prototypical Kubernetes-based manufacturing data and control hub has been developed, which greatly reduces the effort of scheduling and hosting support applications for manufacturing. This computing cluster lays the foundation for automated data streaming of machine sensor data and their analysis by providing computing, storage, and connectivity resources on demand. The system was designed in a way that the ingestion of data streams, the persistent storage of data in databases or data lakes (Rudack et al. 2022), its automated analysis, firewall rules, user rights, and analytics software are all managed by the Kubernetes operator pattern (Verma et al. 2015), which greatly lowers the cognitive load caused by running and maintaining such a system. Even software-controlled manufacturing machines have been managed by this control plane which removes the barrier between Operation Technology (OT) and Internet Technology (IT) completely, since the manufacturing machine's software is deployed, run, maintained, and monitored in the same centralized manner as a cloud-based database or support application. Therefore, the cluster acts as a centralized connector which enables the usage of production data along the complete lifecycle of the production process. The use of open-source software not only avoids vendor lock-ins but also guarantees interoperability between systems. Through containerized software applications and by following established cloud-native principles, our prototype is transferable to any cloud provider. To assess the viability of our infrastructure in production, we connected a 500 t horizontal high-pressure die casting machine and its auxiliary cell systems to a prototypical data lake. This design allows us to experiment with a full-scale physical machine on premises. In particular, we utilize a testbed that includes complex production machinery with multiple PLCs, an edge server, and a dedicated cloud infrastructure (data lake) (Rudack et al. 2022).

(In-)Network Capabilities Today's communication systems follow a strict interpretation of the end-to-end principle (Saltzer et al. 1984), i.e., the network only delivers packets without modifying them (Kunze et al. 2021c). Thus, In-Network Computing (INC) is typically not supported out of the box. Aggravatingly, the exact scope of INC remains undefined, and identifying which domains can benefit most is still an ongoing process (Kunze et al. 2022). Research already investigates how INC can be included in existing communication infrastructures (Kunze et al. 2021c) and what kind of functionality can be provided by INC (Kunze et al. 2022).

The main envisioned benefits of INC for industrial processes are higher data rates and lower latencies as networking devices can process packets at line rate and are located close to the processes. The straightforward latency benefits have already been studied and demonstrated by related work (Cesen et al. 2020), mainly focusing on In-Network Control (cf. ▸ Chaps. 11 "Model-Based Controlling Approaches for Manufacturing Processes" and, "Resilient Future Assembly Systems Operation in the Context of the Internet of Production"). In our work, we investigate which functionality can be enabled by INC in spite of specific hardware constraints.

In modern industrial scenarios, all entities (robots, machinery, etc.) are tracked using various metrology systems, such as iGPS or laser trackers (cf. Chap. "Resilient Future Assembly Systems Operation in the Context of the Internet of Production"). These systems use different formats to capture locations, e.g., using different coordinate systems, and metrology information thus needs to be transformed into a common scheme. In one of our works, we investigate how well the required coordinate transformations can be deployed on programmable networking hardware (Kunze et al. 2021a). While we find that there are indeed challenges requiring heavy workarounds, we also see that INC can achieve low latencies and high accuracy, as well as significantly higher packet processing rates than end-host-based applications.

We further investigate data preprocessing using INC. More specifically, we intend to deploy an INC platform to react to different process phases and dynamically adapt how data is preprocessed and where it is forwarded (Kunze et al. 2021b). In this approach, the INC platform summarizes sensor information in well-defined intervals and uses a local clustering algorithm to distinguish process phases. We offload heavier analysis functionality to a slower control plane which can then define which actions are supposed to be taken depending on the currently identified process phase.

Overall, these approaches showcase that INC can be sensibly used in industrial contexts. However, there are still many remaining questions, e.g., regarding the inclusion of such approaches into existing communication infrastructures (Kunze et al. 2021c), that need to be solved before INC can be widely deployed.

3.3.2 Device Interoperability

To make measuring systems technically interoperable, we aim toward a shift in the role of measuring systems. Instead of considering a measuring system as an integral component of a production process of industrial application, we interpret measuring systems as independent micro-services that offer their services, i.e., the acquisition and provision of measurement values, to different applications and stakeholders. This idea results in the concept of Cyber-Physical Measuring System (CPMSs), creating the basis of modern infrastructures in industry.

We call such a system a FAIR sensor service (Bodenbenner et al. 2021) which is mainly defined by the following three attributes: (i) The CPMS must advertise its offered service and ensure high quality of the provided measurement data, i.e., the data (and the service itself) must conform to the FAIR principles (Wilkinson et al. 2016). (ii) The CPMS senses a change in a physical quantity, quantifies this change as a relative or absolute measurement value of that quantity, and digitizes this value. (iii) For the environment, an interoperable interface characterizes the sensor, which mainly consists of a functional information model and a standardized, manufacturer-independent, and device-agnostic data format and communication protocol.

With that, the interoperability of the measuring device is increased, and the heterogeneity of communication interfaces and data formats is significantly reduced. However, joining those three concerns into one CPMS also increases complexity and requires expertise in three different domains: (i) implementation of the internal sensor logic, (ii) defining a FAIR (meta)data model, and (iii) the development of the communication interface. To decouple these three aspects, we propose a novel three-layer architecture for FAIR sensor services (Bodenbenner et al. 2021) and utilize model-based software development to leverage generalizable parts, as, e.g., the communication interface, by developing a domain-specific modeling language called SensOr Interfacing Language (SOIL) (Bodenbenner et al. 2020). Based on a simple meta-model, the data model of the interface of the FAIR sensor service can be developed without any knowledge of communication protocols and data formats by the developer of the measuring device. Based on the interface description written in SOIL, a template for implementing the internal sensor logic is generated in a general-purpose language (e.g., Python or C++), to which the non-generalizable implementation of the internal sensor logic is injected manually. Furthermore, a RESTful HTTP server and an MQTT publisher are generated, such that there is no additional effort required regarding the connectivity of the measuring device.

To fully realize FAIR sensor services, we are currently researching the automatic generation of metadata schemata from SOIL models, as well as the inclusion of more target languages, communication interfaces, and data formats, which will eventually result in fully, semantically interoperable interfaces as we illustrate in Fig. 3.3.

3.3.3 Data Security and Data Quality

Enriching existing (industrial) infrastructures with appropriate data security requires developments along multiple dimensions. As the most basic mechanism, data usage policies (Henze et al. 2016), which efficiently formulate allowed utilization of sensitive data, allow stakeholders to express their privacy and data sovereignty needs. For example, companies can specify details about the suitability of using

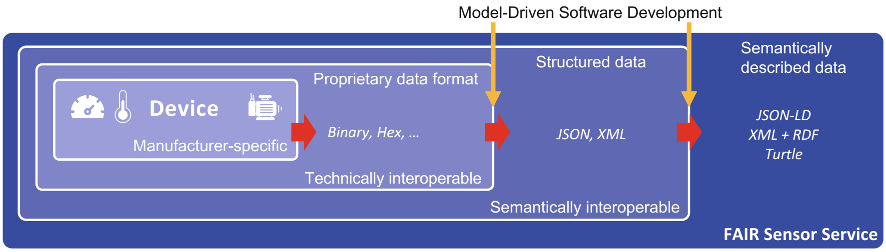

Fig. 3.3 Our proposed interoperability hierarchy of interfaces for Cyber-Physical Measuring System (CPMSs). While manufacturer-specific interfaces are mostly non-interoperable, we can achieve interoperability by providing context information through semantically annotated (meta)data

specific cloud infrastructures (Henze et al. 2020). However, these policies require an underlying physical infrastructure, e.g., a cloud storage system, that is also capable of enforcing them (Henze et al. 2020). Moreover, recently proposed dataspaces still need to work on providing corresponding technical guarantees (Lohmöller et al. 2022).

Thus, complementing the efforts of developing and enforcing data usage policies, we also pursue the research direction to provide technical security guarantees to companies. In particular, to evolve today's infrastructures, we rely on well-known secure building blocks (Pennekamp et al. 2019b) from the area of privacy-preserving computing to implement data security. For example, we rely on attribute-based encryption to realize reliable, yet dynamic access control within supply chains (Pennekamp et al. 2020b; Bader et al. 2021). Similarly, companies can utilize homomorphic encryption (which enables computations on encrypted data) to protect their sensitive information when performing computations on joint data, e.g., in the context of performance benchmarking, without significantly decreasing utility in practice (Pennekamp et al. 2020d). Thus, the presented and related building blocks are well-suited to implement secure offloading (e.g., to cloud environments) in industry.

Moving toward the challenge of ensuring data quality, we propose different mechanisms to improve the accountability of participating companies. First, we employ blockchain technology to establish technical trust anchors (Pennekamp et al. 2020b; Bader et al. 2021; Wagner et al. 2022b). These trust anchors immutably persist data fingerprints to ensure that the covered information is long-term verifiable. They further ensure that companies can be held accountable, e.g., if faults occur during usage of a manufactured product. We validated our approach using supply chains of cars that involved fine-blanked components. Second, when looking at the exchange of information, our novel digital transmission contracts enable companies to prove that a data exchange took place (Mangel et al. 2021), i.e., companies cannot deny their participation at a later point in time. These mechanisms will improve the reliability of shared information as companies must otherwise fear being held accountable.

Finally, when looking at deployed devices at the production site, we explore the potential of utilizing trusted sensors (i.e., sensors equipped with trusted execution environments) to secure the data collection (sensing) in industry (Pennekamp et al. 2020a). Here, the main advantage of our work is a significant improvement in the correctness and authenticity of processed data, which allows companies to secure the full data lifecycle of their products for the first time.

3.3.4 Network Security

To impede cyberattacks against production deployments and thus prevent production outages and harm to humans, implementing strong network security measures is essential. Here, the evolution needs to be threefold: (i) security must evolve with industrial communication use cases, (ii) operators need support in configuring their deployments securely, and (iii) remaining attacks must be detected.

The interconnection of production deployments leads to novel forms of communication which need to be secured. For example, end-to-end secure communication was rather challenging in the novel publish/subscribe paradigm for industrial communication. With our approach ENTRUST, which transparently enables end-to-end secure communication and integrates seamlessly into existing infrastructures, we allow future publish/subscribe deployments to communicate end-to-end secure (Dahlmanns et al. 2021). Likewise, the unique characteristics of industrial settings and especially the resource constraints of industrial devices require adapting traditional security paradigms, especially in wireless settings. Our research work, e.g., allows us to efficiently realize message authentication for short messages (Wagner et al. 2022a) or to speed up the computation of message authentication tags in the latency-critical input-dependent part through bitwise precomputations (Wagner et al. 2022c).

From a different perspective, the increase in security mechanisms and protocols equally makes the security configuration of deployments more complex and thus challenging. Hence, operators need support in regularly assessing their current security configuration with regard to the current security landscape and require assistance in configuring their industrial deployments securely. As most of today's assessment tools lack support for modern industrial protocols, e.g., OPC UA, we designed and developed an open-source plugin for the state-of-the-art pentesting software Metasploit that supports operators in analyzing the security of their deployments (Roepert et al. 2020). To support operators in realizing secure configurations, e.g., when a security assessment identifies deficits, up-to-date configuration templates can assist operators by making best practices easily and actionably accessible (Dahlmanns et al. 2022). However, our research shows that such templates should never include any example credentials, since operators often unknowingly do not exchange them and consequently severely weaken their own security (Dahlmanns et al. 2022).

Besides all preventive security measures, intrusion detection and prevention systems are needed to thwart any remaining, especially unknown, attack vectors.

While recent research provides sophisticated approaches leveraging semantic and process knowledge, these approaches rarely find their way into practice, mainly due to their tight coupling to distinct industrial communication protocols and individual datasets. By leveraging commonalities found in industrial communication, our research lays a common ground for realizing widely applicable industrial intrusion detection systems (Wolsing et al. 2022). Furthermore, state-of-the-art industrial intrusion detection systems typically rely on machine learning to detect anomalous behavior. While these systems achieve, in theory, extremely high detection accuracy, in practice, they often miss unknown attacks. To overcome this false sense of security, our novel evaluation methodology assesses whether industrial intrusion detection systems are indeed able to detect attacks they have not been trained on and identifies significant room for improvement to realize efficient and effective machine learning-based industrial intrusion detection systems in practice (Kus et al. 2022).

3.3.5 Infrastructure for Secure Industrial Collaboration

When evolving the production landscape from localized production sites to a globally connected WWL that directly influences decision-making, significant research efforts are needed to realize an infrastructure for industrial collaboration in a secure and privacy-preserving manner. The underlying goal of industrial collaboration is to unlock all available data sources from different stakeholders in real time (Pennekamp et al. 2021b). To implement such a disruptive change within the industrial infrastructure, we envision the gradual implementation of different applications (with increasing levels of automation), as we illustrate in Fig. 3.4.

First developments will tackle use cases without automated process adaptation, i.e., initially, the infrastructure must provide means to compare information between stakeholders without directly interfering with running processes (Fig. 3.4, left). Here, a goal can be to provide companies with insights into unrealized potentials

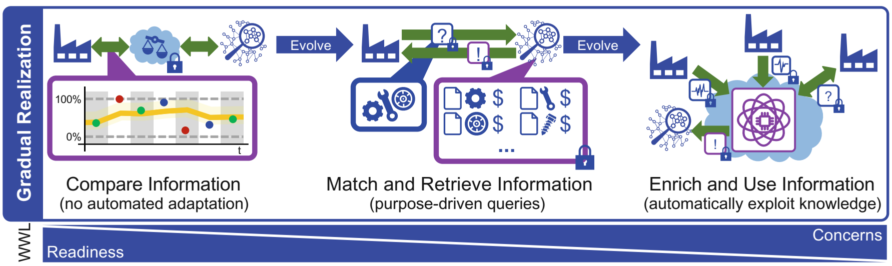

Fig. 3.4 Industrial collaborations will be realized gradually. An increasing level of automation requires new approaches and building blocks. Simultaneously, the evolution of the infrastructure will increase the stakeholders' concerns as the sourced technology is not yet proven and tested

by comparing their business performance or process decisions. We exemplarily realized such an architecture using homomorphic encryption (i.e., computations on encrypted data) to preserve confidentiality while performing comparisons alongside various key performance indicators (Pennekamp et al. 2020d). As another application, we are currently pursuing a new secure and privacy-preserving concept to support companies during the establishment and identification of new business partners to account for the dynamic nature of the IoP and the increasing necessity of quickly reacting to customer change requests (Pennekamp et al. 2021a).

Subsequently, moving toward an infrastructure that allows companies to directly improve their local processes by incorporating external information, i.e., by effectively tearing down today's established data silos, requires significant changes to the information flows in industry. To demonstrate the adequate and purpose-driven matching of information, we designed a platform that provides companies with an approach to exchange production process parameters while keeping their sensitive information and queries private (Pennekamp et al. 2020c). Using secure building blocks (oblivious transfers, private set intersection, and Bloom filters), we can keep all information private until an explicit match has been made by a querying company. In general, purpose-driven queries need to be matched with data using semantic information to allow for meaningful process improvements (Fig. 3.4, center).

Moving forward, the physical infrastructure underlying the IoP is envisioned to evolve into a direction that allows companies to directly feed new insights from external information into their processes (Fig. 3.4, right). In this context, (cloud-based) federated yet privacy-preserving machine learning constitutes a key research direction that promises direct implications on industrial control loops or adapted production planning. Consequently, these novel information flows must be supported by the underlying physical infrastructure to enable these new collaborations.

3.4 Conclusion

The underlying infrastructure from the sensor to the cloud serves as the foundation of and key enabler for the Internet of Production (IoP) and facilitates the use of its internal multilayered components, such as digital shadows, data lakes, and the World Wide Lab (WWL). The transition from sparsely connected production machines, cells, and sites with mostly isolated and incompatible computing nodes and data silos to an interconnected IoP requires a fundamental redesign and evolution of the underlying infrastructure. We identified open challenges in five research areas for the *Infrastructure of Production* that prevent the realization of the IoP with its distinct requirements for the underlying infrastructure in practice. These issues include limitations rooted in today's security and network architectures across production sites as well as challenges related to the involved computing paradigms, such as edge computing, in-network computing, and the overarching cloud computing. Further research is needed on how to facilitate the secure interaction of network devices, machines, and sensors to enable low-friction collaborations between different stakeholders. All of these challenges must be solved to finally establish the IoP since an adaptable, interoperable infrastructure serves as the enabler for the construction of digital shadows, their exploitation via downstream applications, and a thriving WWL. Related industrial paradigms and research without a connection to the industrial domain, both largely being without the required access to domain expertise, cannot make up for the outlined shortcomings and research gaps.

In this work, we discussed our research agenda and goals on a more general level. However, some key aspects of previous and ongoing research especially exemplify our contribution to the evolution of the industrial landscape and, in particular, the IoP with its unique processing and security requirements. Additionally, we can source from a plethora of realistic real-world use cases, which allow us to approach research challenges in a goal-oriented manner. Our work on coordinate transformations, e.g., demonstrates that novel networking paradigms can be effective solutions for the specific challenges of metrology systems (Kunze et al. 2021a). Moreover, we illustrated how to utilize generative software development to reduce the integration effort of measuring systems by generating interoperable communication interfaces based on a unified data model (Bodenbenner et al. 2020). To further address data security requirements in situations with dynamic business relationships (as envisioned in the WWL), we developed a design that enables companies to share product and production information flexibly and securely (Pennekamp et al. 2020b). Our direct ties to industry even allowed us to evaluate this design using a real-world use case covering an electric vehicle production (Bader et al. 2021). Derived from requirements for secure communication inside envisioned future production plants, we proposed ENTRUST, a novel solution to transparently end-to-end secure publish/subscribe communication (Dahlmanns et al. 2021). Finally, our interdisciplinary research environment allows us to pursue visionary and possibly disruptive ideas. One prime example is our developed parameter exchange as it securely realizes flows of information that currently do not exist in industry due to confidentiality concerns. Such efforts underline the value of research into an *Infrastructure of Production*.

Building on these first advances, we specifically regard our planned in-network process phase detection with its subsequent adaptable data preprocessing (Kunze et al. 2021b) as a promising next step. We intend to show how to directly transfer the latest advances in networking to use in industry, despite the limitation that such initial concepts do not yet exploit the IoP's full potential. In the future, we strive to continually evolve our outlined research areas to advance the general evolution of industrial infrastructures to effectively transform them into a securely and globally interconnected *Infrastructure of Production* with access to a prosperous WWL.

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A Digital Shadow Reference Model for Worldwide Production Labs

4

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Abstract

Due to their growing amount and heterogeneity, we need a precise and standardized understanding about the foundation, structure, and forms of aggregation and especially the use of data and models within the production domain. Our aim is to investigate how to model data elements and static and dynamic relationships as well as their physical resources in the IoP, in a cross-disciplinary life cycle spanning cooperation as a basis for information management, meeting all technical, scientific-ethical, and legal framework conditions. The core solution for this challenge is the use of an adequate set of modeling techniques, transformations, and their integration with digital shadows. This chapter provides a deep insight into relevant concepts that constitute a digital shadow, link it to their semantics defined by appropriate metamodels, and discuss the data and models a digital shadow consists of in four use cases. We show a method to derive digital shadows and introduce their life cycle in relation to the product life cycle. These concepts are the foundation for data and model sharing within digital shadows applicable for worldwide production labs.

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4.1 Introduction

Motivation Handling the ever-growing amount of heterogeneous data and models within the production domain (Brauner et al. 2022) requires a precise and standardized understanding about their foundations, structure, and forms of aggregation and especially their use. Managing quantities of data in structured form requires (1) pre-aggregation and cleansing of data for analysis, (2) which can be used within and across overall industrial ecosystems, (3) which are organized and contextualized according to metamodels to become self-contained and explainable, (4) where the metamodel is sufficiently precise and detailed, and thus finally (5) usable for derivation of algorithms and other forms of code, e.g., through model-based code generation. Our approach to handle these requirements is the concept of digital shadows (DSs). In our understanding, "a digital shadow is a set of contextual data traces and their aggregation and abstraction collected concerning a system for a specific purpose with respect to the original system" (Becker et al. 2021). These digital shadows can be used for sharing data or within software systems such as digital twins (DTs). For us, a digital twin is "a set of models of the system, a set of digital shadows and their aggregation and abstraction collected from a system, and a set of services that allow using the data and models purposefully with respect to the original system" (Dalibor et al. 2020). We create DTs as active software systems for observable objects and systems in the physical world that can be monitored, sensed, actuated, and controlled. However, due to the vast amounts of data that a virtual representative of a product, machine, or production line would require, a complete digital twin is not feasible (Brauner et al. 2022). Digital shadows provide us the needed information about a system's state and history for a specific purpose which could be used within DTs. In contrast to DTs, however, they are a passive set of data (Brauner et al. 2022) and do not directly influence the physical system or objects (Kritzinger et al. 2018). To use digital shadows, we need a good understanding of relevant concepts, the methods to use them, and how they can be applied in different domains.

Current research lacks detailed descriptions about what constitutes a DS and how to create and maintain them. Existing research covers only parts of the DS concepts, e.g., metadata (Quix et al. 2016), data management and concepts from artificial intelligence (AI) (Liebenberg and Jarke 2020), data and data analytics (Ladj et al. 2021), or production processes and resources (Schuh et al. 2019). To cope with that, we suggested a first version of a conceptual model for digital shadows in Becker et al. (2021), which has to be further evolved to meet different use cases.

Research question Within this chapter, we tackle the question of how to model data elements and static and dynamic relationships as well as their physical resources within the Cluster of Excellence "Internet of Production" (IoP) in a cross-disciplinary life cycle-spanning cooperation as a basis for knowledge management while meeting technical, scientific-ethical, and legal framework conditions.

Contribution The core solution for this question is the use of an adequate set of modeling techniques, transformations, and their integration with DSs. This chapter provides insight into relevant concepts that constitute a DS and link it to their semantics defined by appropriate metamodels. This includes related assets and their properties described by engineering models, relevant data organized in data traces, data points and metadata as a source for calculation, and simulation for a specific purpose. We propose and discuss the digital shadow reference model (DSRM) in its second version that is based on Becker et al. (2021) and includes heterogeneous system configurations as well as engineering, calculation, and simulation models. To support interoperability, we discuss digital shadows in relation with base and domain ontologies. As the design of a digital shadow data structure is challenging in practice, we propose a stepwise method to derive a digital shadow from existing data. Moreover, we provide usage evidence in the form of examples from (1) production planning in injection molding, (2) process control, (3) laser-based manufacturing, and (4) automated factory planning discussing relevant digital shadow data models and semantics. Moreover, we discuss data and model life cycles in relationship to digital shadows and provide an outlook into open challenges for digital shadows and their use, especially within digital twins of the Cyber-Physical Production Systems (CPPS).

Structure This chapter is structured as follows: Sect. 4.2 discusses related work for digital shadows. Section 4.3 presents the digital shadow reference model, and Sect. 4.4 discusses the role of ontologies for DSs. We present in Sect. 4.5 four use cases and their use of digital shadows and propose a method to derive a digital shadow from the domain expert perspective in Sect. 4.6. Section 4.7 illustrates the need for extended life cycle of production data and models. Section 4.8 gives an outlook to the use of digital shadows in digital twins before the last section concludes.

4.2 State of the Art

Clearly, digital shadows are important concepts for data use and sharing in smart manufacturing (Brauner et al. 2022). Thus, there exist several publications about digital shadows, and some parts of their most relevant concepts are already defined in other contexts.

Data and Metadata Management Quix et al. (2016) describe their conceptual view on a metadata model that suits for the extraction of metadata and its management in data lakes. In (2020), Liebenberg and Jarke make use of generalizations of database view conceptualizations to model digital shadows regarding AI and data management aspects in the IoP. In contrast, our DSRM uses additional information and contextualizes data, for example, by specifying the source it originates from, or the asset by connecting it to its engineering models.

Loucopoulos et al. (2019) presents a conceptual metamodel for cyber-physical production systems, focusing in particular on aspects of information exchange and analysis at a wide level of requirements engineering. However, it does not address the standardization and detail level presented in this chapter.

Modeling the Production Domain Bravo et al. (2008) present a metamodel that allows describing business objects. For that they enriched the metamodel presented in the PRDOML (www.prodml.org) Reference Architecture by the elements of resource, execution, planning, product, and client. In comparison to this approach, we look at the asset of the given physical system, its unique purpose, and the enrichment with metadata.

Ladj et al. (2021) describe a self-learning, continuous improving, and knowledge-based digital shadow incorporating a physical as well as a virtual system. The digital shadow manages data and knowledge. For that, they present a framework that applies data analytics to the database. The digital shadow uses the generated knowledge base to support the decision process. Their approach defines the purpose of the physical machine but is missing an extendable description of the elements contained in a digital shadow.

Bauernhansl et al. (2018) propose a concept for DSs of production. The core function of the DS is to provide the required information and is considered as a macro-service consisting of different micro-services, which guarantee to provide the right information at the right time and place. Necessary services are, e.g., control of information flow, a record of user needs, and identification or compression of information. The development of digital shadows is described by four complexity levels: linkage of information, information flow control, information quality control, and feedback and self-optimization of data and information basis. Bauernhansl et al. (2018) describe core functions but no conceptual model for digital shadows is given.

Schuh et al. (2019) develop a data structure model for digital shadows in the order fulfillment process from order acquisition to work preparation of single and small batch productions. The digital shadow is prerequisite for managing the organization's knowledge that can be utilized to solve the use-case-specific tasks. The proposed data structure model describes relationships between relevant objects in the order fulfillment process, e.g., product specifications, manufacturing and assembly processes, and production resources. The data structure model digitally represents the real processes of single and small batch production, thus outlining the role of digital shadows for the use of knowledge management systems. However, the research is limited to the design of a concrete model for a specific use case, while no conceptual model is given. In addition, concepts such as purpose or data sources are not considered.

Parri et al. (2021) developed an architecture around digital twins using a model-driven approach to derive structural configuration times from SysML Block Definition Diagrams. A digital twin instance contains a concrete configuration that contains macrosopic events such as a failure event. They, as well, modeled a metamodel as a UML class diagram of the knowledge base concentrating on the digital system of a company and do not model elements of the digital shadow such as the contextualized data or models used.

Modeling Further Domains Croatti et al. (2020) describe a metamodel for agent-based DTs in healthcare. The main elements of the metamodel are the digital twin and the physical asset connected by a cyber-physical connection. The model describes the physical asset for the DT, which interacts directly with information sources. Their metamodel is described at a high level and does not consider data traces.

Mertens et al. (2021) discuss to extend the concept of digital shadows to humans. This approach could be used for human-robot collaboration for manual work, decision support, and work organization, as well as human resource management. However, a concrete description of the relevant concepts is up to future work.

We took the insights gained from this related work and incorporated shortcomings into our digital shadow reference model. One point that particularly sets our approach apart is the consideration of connections to existing models, e.g., system, simulation, or AI models. Furthermore, we provide an additional semantic layer by pointing out the usage of ontologies along with DSs, give examples of digital shadows utilized in industrial use cases, and provide a methodology on how to build digital shadows from scratch.

4.3 The Digital Shadow Reference Model

In Becker et al. (2021), we suggested the first version of a conceptual model for digital shadows. This model comprises the ideas in our understanding of a digital shadow (see Sect. 4.1) for purposefully collecting, aggregating, and abstracting data from production enriched with meta-information to enable fast decision-making. As additional use cases employing DSs were realized for use in the IoP and further exchanges regarding its modeling best practices continued among the researches, the conceptual model for DSs was refined. The current version is defined in the digital shadow reference model, which is shown in Fig. 4.1 as a UML class

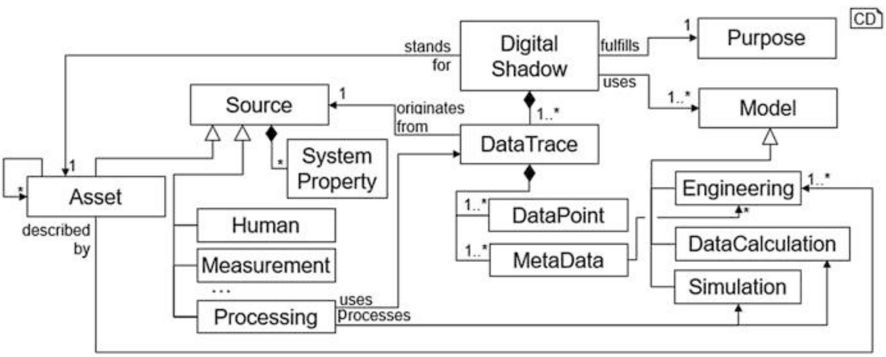

Fig. 4.1 The refined digital shadow reference model

diagram (Rumpe 2016). The DSRM is intentionally underspecified and only models key elements. A digital shadow designer is free to extend the DSRM to achieve a DS model tailored to their use case. The digital shadow collects aggregated and reduced data from an original system with respect to a specific purpose. Therefore, the digital shadow knows its referencing asset and the purpose it fulfills. It is composed of data traces that contain single data points. Those data traces originate from a source (e.g., the original asset) and are enriched with additional metadata. The digital shadow uses models to describe the system, data calculations, or system simulations.

Models play a key role in the reference model. According to Stachowiak (1973), models (1) consist of a mapping to an original object that the model represents, (2) are reduced to the relevant aspects and abstract from details of the original, and (3) have a pragmatism that lets them replace the original in certain scenarios. They add an abstract representation of knowledge of the underlying system and describe calculations for, e.g., data aggregation or simulation, and help to evaluate the asset's data by providing more context. We initially distinguish between *Engineering*, *Data Calculation*, and *Simulation* models. Engineering models arise during design time of the physical asset to plan the system's structure and behavior. Proper modeling of the target system during design time allows for a consistent, quality ensured development. In model-driven software engineering, models can also be used to generate code from an abstracted view on domain knowledge. These models then can be reused in the digital shadow to provide additional information to manufacturing data and to outline the system. UML class diagrams to describe the structural elements of an asset together with object diagrams to describe the asset's layout and the Object Constraint Language (OCL) to restrict possible values and layouts are utilized to represent large parts of the asset. Ontologies and SysML BDD (Weilkiens 2011) models have similar expressiveness regarding the asset's structure. Architecture modeling, such as MontiArc (Dalibor et al. 2020) or Focus, targets the system's components in the large as well as their interconnections and communication. Behavior models, like state machines or MATLAB's Simulink (Mathworks: Simulation and Model-Based Design https://www.mathworks.com/products/simulink.html), provide information about the asset's expected behavior. The digital shadow uses *Data Calculation* models to formulate data aggregation and can have any form, from workflow models (Freund and Rücker 2012) over programmed Excel tables to complex optimization models as Python script. *Simulation* models serve in a similar function but with a strong focus on living aside with the physical asset and predict behavioral aspects. In that sense, *Data Calculation* models are meant to be executable by some engine, mainly a processing component, to compute new data traces. Results of both *Data Calculation* and *Simulation* models can be used by one another and finally provide an abstracted view on the manufacturing data.

A digital shadow is designed for fulfilling exactly one specific *Purpose*. The *Purpose* is the basis for data acquisition and information generation and varies from a human-formulated text string or selected filter criteria to semantically defined ontology terms. The detail level of the *Purpose* determines the range of the decision support, and subsequently the consideration of assets, models, and sources. Usually, the more general a purpose is formulated, the more results a requester gets. For example, finding an optimal shop floor configuration in general leads to multiple results since different objectives are competitive, e.g., costs and adherence to the jobs' due date. Moreover, different models can fulfill the same purpose and hence lead to different results for the same purpose. An example in the production domain is finding the optimal lot size of a purchase order where different suitable models like Andler, Groff, or Silver-Meal exist (Vahrenkamp 2008).

To fulfill its purpose, DSs gather data from a *Source* that supplies at least one data point. Sources can be differentiated into *Assets*, manual inputs from *Humans*, automatic *Measurements* from sensors, data *Processing* (i.e., cleaning, aggregation, simulation, or calculation), and other digital shadows. *Sources* are further specified by *SystemProperties*, which define attributes of a source at a given point in time.

An *Asset* "is an item, thing or entity that has potential or actual value to an organization" (DIN ISO 55000:2017-05 2017). Thus, an asset can be either of physical or virtual manner. Typical physical assets on the shop floor are machines, equipment, material, or finished goods, while typical virtual assets comprise jobs, routings, bill of materials, machine settings, or drawings. Assets can be described by engineering models that provide their properties. The *SystemProperties* specify the assets' technical feasibilities and conditions at a point in time, like status or performance. The composition of multiple assets can lead to a new asset, e.g., the combination of a machine and a handling robot to a work center, and subsequently to new properties, e.g., the overall equipment efficiency for this work center. The prerequisite for an automatic decision support through DSs is a digital representation of the assets' properties in the digital world, e g., within a software system like an enterprise resource planning, which comprises the assets' master data. Moreover, especially for transaction or process data (such as confirmation of jobs and current temperature), *Humans* via plant and *Measurements* via machine data acquisition realize the data flow. Because the gathered raw data for models is often not suitable for direct processing, *Processing* as an essential source is introduced for building and/or calculating the traces. Therefore, *Processing* can use previously built data traces or processes gathered data from other sources, i.e., by the filter, aggregation, simulation, or calculation. Thereby, digital shadows can also act as a source.

The digital shadow captures data derived by *Sources* as *DataPoints* gathered in contextualized *DataTraces*. Each *DataTrace* describes one procedure of this *Source*, which it is connected to and is a subset of the available data. Single *DataPoints* are used by the DS to provide information regarding the target purpose and are either directly accessible or may contain a reference to the original data. *MetaData* enrich *DataTraces* with additional information over its creation process, e.g., its creation time, or further structural knowledge. Combined with the *SystemProperty*'s validity in time, the *DataTrace* can be mapped to a specific system configuration of the referenced *Asset* or other *Sources*. This way, much more context is given to a *DataTrace*: its originating source can be the asset itself, processings on other data traces, or even other digital shadows; and *MetaData* together with the system configuration provide a clear context of its creation.

4.4 Ontologies in the Internet of Production

One of the challenges of interdisciplinary collaboration is making knowledge available and interpretable so that insights can be transferred and used in other domains. The digital shadow reference model presented in Sect. 4.3 allows to overcome these challenges by using a unified model to communicate different data structures. However, it is not sufficient to ensure smooth communication between different domains. Without the necessary semantics, these data often lack interpretable context and tend to be rigid and without any possibility to adjust the level of detail. Ontologies are a useful tool from the Semantic Web introduced in Berners-Lee et al. (2001) to enable accurate modeling of real-world objects at any granularity and to build explorable knowledge bases by semantically linking data. At the same time, data is offered in machine-readable form and can be interpreted and further processed with the help of the corresponding ontologies. In addition, ontologies enable the creation of universally valid metamodels that can be flexibly applied to different use cases, as presented in Sect. 4.3. Ontologies and Semantic Web technologies have gained great importance in the IoP. Due to their flexible application possibilities, ontologies are not only used as a modeling tool, but find practical application in many different research areas. In the context of the IoP, our previous work Lipp and Schilling (2020) identified and evaluated the application domains depicted in Fig. 4.2. Applied methods include but are not limited to ontologies for modeling, the SPARQL Protocol and RDF Query Language (Prud'hommeaux and Seaborne 2013) for querying, the Shapes Constraint Language (SHACL) (Knublauch and Kontokostas 2017) for validating, and tool support for visualization and search. In the following, we present these five areas with references to application examples. Please refer to Sect. 4.5 for a more detailed presentation of selected use cases that build on ontologies and DSs.

(A) Data/service catalog is a widely used application and an excellent way to structure any given data source such as dataset, services, participants, or projects. They help users to keep track of a large number of different sources and enable them to find information based on different search terms. Open data portals for Germany (Geschäfts- und Koordinierungsstelle GovData: https://govdata.de) or Europe (Publications Office of the European Union: https://data.europa.eu) are a prominent examples of how data catalogs are used. A catalog usually is independent of the data itself and is applicable to any data management system. In the context of the Internet of Production, data catalogs can be used to make data available between domains. Catalog ontologies such as Data Catalog Vocabulary (Albertoni et al. 2019) are used as a basis for uniform communication and thus to improve interoperability. In addition, unique and persistent identifiers simplify automatic processing of sources.

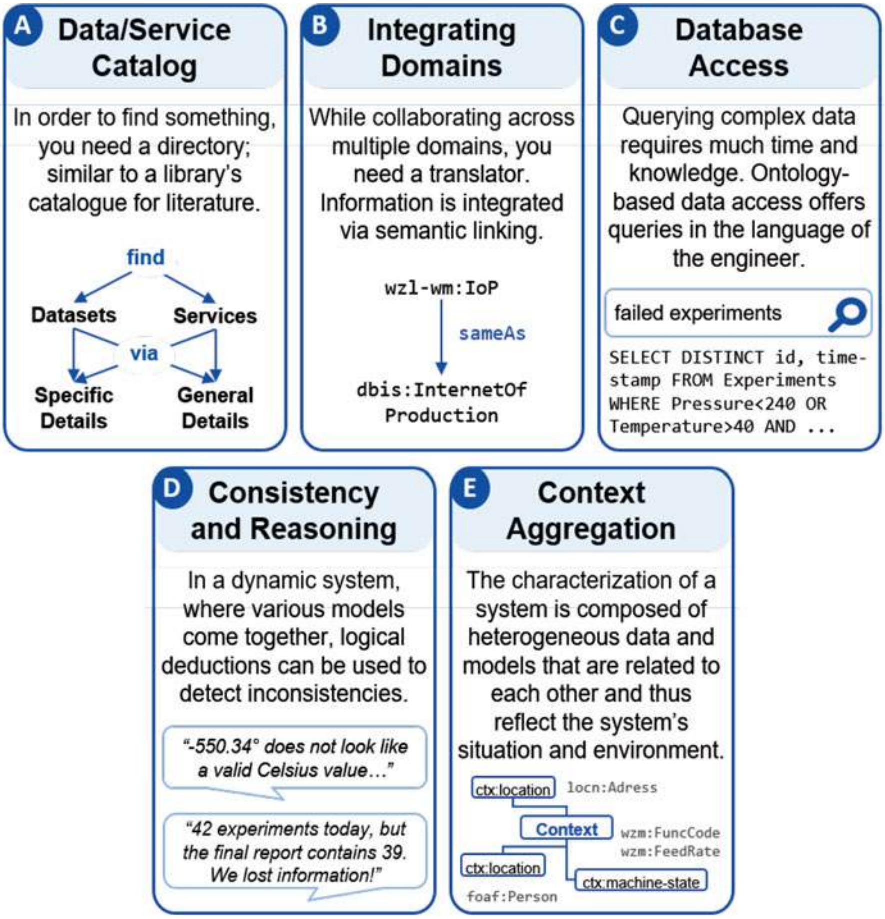

Fig. 4.2 Main application areas of the Semantic Web in the IoP (Lipp and Schilling 2020)

(B) Integrating domains enables human understanding data and enhances interoperability on machine level. It is common practice to reuse existing ontologies to create a shared knowledge among different domains. However, it might still be necessary to extend ontologies or create new ones to optimally serve respective use case. Suggested tools include the widespread fully fledged ontology editor Protégé (Noy et al. 2001) or our quick prototyping tool Neologism (Lipp et al. 2021), which also allow combining multiple ontologies. One can, for instance, align concepts within one or multiple ontologies using constructs like `sameAs`/`broader`/`narrower` or apply more semantically sophisticated methods (Lipp et al. 2020a).

Ontology-Based Data Access (OBDA) enables *(C) Database Access* by using semantic tools. By mapping concepts of ontologies to terminologies and relations of data base schemas, domain experts are enabled to access data relatively easy and without further database knowledge.

(D) While *Reasoning* infers new knowledge from existing information, *Consistency* checks and validation in general enable safe system interfaces and predictable data processing. Lightweight Semantic Web Services for Units (LISSU) (Lipp et al. 2021), for instance, used in Sect. 4.5.3 provides validation for service-oriented architectures and Theissen-Lipp et al. (2022) extends this approach to an integrated SHACL-based solution.

(E) Data aggregation combines arbitrary, heterogeneous environments into a joined source of information and enables advanced semantic analysis based on views using different abstraction, focus, or interpretation. This approach is similar to the concept of DSs and was applied in Lipp. et al. (2020) to optimize data collection from manufacturing systems, in Lipp et al. (2020b) to even aggregate collected data and metadata into a data lake, and in Sect. 4.5.1 to support decision-making processes.

The abovementioned technologies maximize their benefits through close communication between all relevant stakeholders, which fosters common understanding and interoperability. The IoP, for example, maintains an *Ontology Expert Group*, where experts from different domains and use cases collaborate on ontologies, tooling, and best practices. This completes the layers of ontologies' benefits from high-level conceptual human understanding to deep technical integration of low-level machine interfaces. The advantages include global unique identifiers, improve (re)use and maintainability of both information and domain knowledge, and finally dramatically improve analysis results through semantic integration of cross-domain solutions.

In summary, ontologies have a wide range of applications. The different main application areas provide new approaches to overcome existing problems in the industry. By using semantic interpretable models like the digital shadow from Sect. 4.3, not only can cross-domain communication be improved, but also a common knowledge base can be created by integrating different domains and thus supporting decision processes across domain boundaries. In the following section, we will show how ontologies and semantic tools can help to overcome existing problems in different use cases.

4.5 Data, Models, and Semantics in Selected Use Cases

To test the applicability of the DSRM, we analyzed data, model, and semantics of four use cases on different levels of details, namely, production planning, and process control in injection molding, adaptable laser-based manufacturing, and automated factory planning. We present relevant concepts, show how digital shadows can be used, and discuss its potentials and challenges.

4.5.1 Production Planning in Injection Molding

Digital shadows are able to support decisions-makers within production planning and control (PPC) in their daily business. We demonstrate different challenges within the domain of PPC in injection molding and how semantics can face those challenges.

PPC facilitates all organizational steps for manufacturing a product, starting from procuring raw materials and ending with the shipment of the finished goods to the customer. Production planning tasks comprise a long-term horizon, i.e., weeks until months. A typical task within production planning is the scheduling of the manufacturers' resources under consideration of due dates, costs, energy consumption, and much more. In contrast, production control tasks are in a short-term manner. Thus, the regarded time horizon comprises seconds until days. One core task in production control is the reaction to disruptions or changes within the production (DIN EN 62264-1:2014-07 2014; Jacobs et al. 2018).

Injection molding is a widely used primary shaping production process with a large variety of possible finished parts to be manufactured. First, the raw plastics granulate is plasticized. Then, the injection molding machine injects the required melt into a mold that comprises at least one or more cavities representing the negatives of the manufactured part. After its solidification, the machine ejects the part, which is then, in most cases, ready for post-processing or dispatching (Rosato et al. 2000).

Figure 4.3 schematically illustrates the elements and their connection that construct a PPC decision support in the injection molding domain.

An operator needs a decision for a complex planning or controlling task that is compliant with a specific *purpose*. In the first step, the operator selects, for example, the scope (e.g., the machines, time horizons, articles) and the optimization criteria. Based on these criteria, the digital shadow selects different but suitable *models*. The prerequisite for this consideration is a classification of the models, i.e., based on optimization objective (e.g., minimization of tardy jobs), in the form of a model catalog. Furthermore, the model catalog specifies the required raw

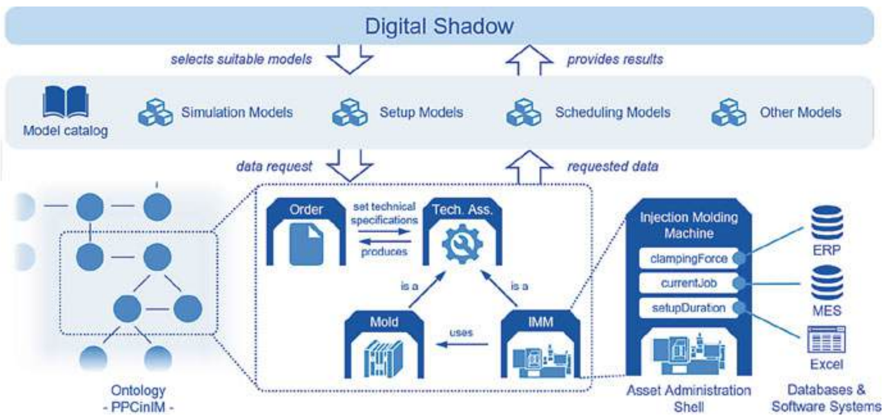

Fig. 4.3 The digital shadow provides decision support for production planning and control purposes in the injection molding domain under consideration of semantics

data for each model, e.g., the jobs' planned start date or quantity. Enabling the transformation from information to data and vice versa under consideration of the right models is coupled to diverse challenges. On the one hand, digital shadows must know which models fit for fulfilling the given purpose and the *source* of the required data. On the other hand, PPC tasks are often complex as multiple *assets*, objectives, and constraints interact in a way that optimization of one objective often causes a trade-off to another objective. A prominent example is the "dilemma of production control," where increasing the (machine) utilization leads to higher work-in-progress inventory (Wiendahl and v Wedemeyer 1993). Hence, PPC is often subject to multiple concurrent objectives leading to a set of optimal solutions, known as Pareto front, instead of one optimal solution. In addition, finding an optimal solution in a short time for a given objective might not be possible due to the vast amount of permutations, e.g., for building a schedule. In this case, the operator desires the providence of a suitable solution (Hopp and Spearman 2008).

Realizing autonomous processing of models requires a digital data representation. This digital representation is enabled through Asset Administration Shells (AASs), as they comprise all relevant *properties* for integration of assets into the virtual world. The AAS can either store the data directly or provide the endpoint for properties located in external databases, e.g., enterprise or shop floor management systems (ERP and MES), manually in excel sheets, or other specialized systems, e.g., warehouse management. Thus, the AAS acts as a single source of truth. Consequently, the operator relies on tools that provide data-based decisions in an adequate time from different data sources.

An ontology establishes the relation between the single AASs. Ontologies and AASs encourage a semantic enlargement for properties with meta-information, e.g., by adding the unit, synonyms, or the description of the properties' meaning, corresponding to IEC 61360. Besides, introducing internationalized resource identifiers (IRI) for each property ensures a unique identification. If all elements (databases, AASs, ontologies, DSs) use IRIs, a modular composition of digital shadows can be realized since the IRIs connect the required data from the model catalog with the AASs and the corresponding databases.

In summary, digital shadows, in combination with semantic tools like AASs and ontologies, are helpful to master the high complexity of PPC and provide data-based decision support to operators. Perspectively, identifying the data and models via IRIs enables a modular integration of DSs that are independent of underlying databases or software systems.

4.5.2 Process Control in Injection Molding

Besides digital shadows for PPC at shop floor level, DSs also offer additional value at control level for many applications in production. In a plastics processing company, digital shadows can be used for monitoring and control of injection molding machines.

Disturbing influences, such as fluctuations in environmental temperature and humidity or changes of material batch composition, influence the injection molding process, which leads to cyclically and long-term variations of part quality (Kazmer and Westerdale 2009). Therefore, it is necessary to continuously adjust the machine settings in order to ensure high reproducibility and avoid rejects.

Process data from the cavity, as location of molded part creation, has a high correlation to part quality. The cavity pressure is referred as the fingerprint of the injection molding cycle and has a great potential for high process stability as control variable (Yang et al. 2016). For instance, a digital shadow, based on model-based predictive cavity pressure control, can be used to compensate process disturbances. A predefined cavity pressure reference is realized by adjusting the screw velocity, whereas the reference is adapted when process disturbances are detected (Stemmler et al. 2019; Hornberg et al. 2021; Vukovic et al. 2022). The main DS concepts and relations of this process control method are shown in Fig. 4.4.

As *purpose*, the digital shadow should realize the given cavity pressure curve with high control accuracy. Needed data originated from the main *asset*, injection molding process, which is divided in the sub-assets mold, machine, material, and human. All process data needed for this DS purpose is collected in the process *data trace* and divided in process *data points* and *metadata*. The process *data points* are updated for each control timestamp in real time and provide actual process

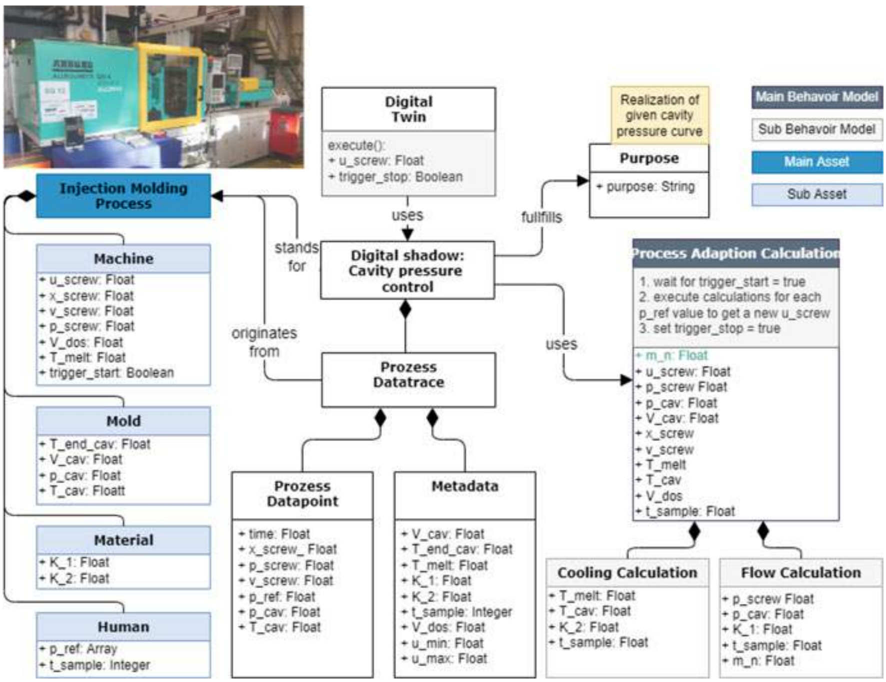

Fig. 4.4 Model of a digital shadow for process control in injection molding

data. *Metadata*, which contains information about mold, material, and machine settings, consists of constant values, which describe the injection molding process and are needed to fulfill the purpose. The whole *data trace* is used for process adaption calculation. Cooling calculation and flow calculation are performed until the injection process ends. A digital twin operates as an external machine control and directly adapts the screw velocity to realize the DS's purpose.

The implementation as digital shadow has several advantages for further usage of the DS in other processes. All data needed for the digital shadow is described in the sub-assets, so the requirements for execution of the DS are given. It follows that the digital shadow can be reused for other processes, if all input data is given. The reusability includes changes of cavity pressure reference curve, machine, material, and mold (produced part). Additionally, changes in the control algorithm can easily be implemented by changing the used *model*.

The data structure of the assets can be reused as well. Further process information can be added to the assets to increase the usability for a wide range of use cases, such as quality prediction based on actual process data. The data traces of each digital shadow only consist of data, which is needed for DS's purpose. For implementation, a classifier can be used, which contains whether the data has to be considered for the DS data trace as process data point or metadata. Otherwise, data will be saved as system properties. This leads to an increased usability as the operator only has to provide data needed. Besides that, it is possible to trace which data and models were used to derive DS's purpose, thus ensuring traceability.

In summary, the application of digital shadows at control level was illustrated by the example of the process control of an injection molding machine. The main advantages of digital shadows are (re)usability and traceability, as data structures and models can be applied to other use cases with reduced amount of effort and high transparency.

4.5.3 Adaptable Layerwise Laser-Based Manufacturing

One of the largest advantages of laser processes is that laser light is weightless and contact-free. These properties make laser light extremely attractive for production systems since these systems are typically not bound to any wear, can deposit the exact amount of energy needed at a precise time and place, and can be reprogrammed for new purposes on demand, making it a perfect digital process (Poprawe et al. 2018). This combination of properties renders laser-based manufacturing systems like Ultra Short Pulse (USP) ablation or Laser Powder Bed Fusion (LPBF), which is a very versatile and flexible manufacturing technology which allows the reconfiguration of production on demand.

These manufacturing technologies typically work in layers. In LPBF 3D printing, e.g., a 3D object is formed by selectively melting one layer of powder on top of another layer. This production process is in concept very similar to USP where the material is removed instead of added forming a 3D negative, e.g., for surface finishing. This layerwise production benefits tremendously from the introduction of

DSs since these discontinuous processes have the inherent feature of having to stop in between layers. In LPBF, e.g., this stop is needed to apply new powder. During this time, a digital shadow can be used that, for example, evaluates the used process parameters during runtime by analyzing the produced surface roughness through camera pictures (Knaak et al. 2021). We can therefore build a digital shadow of a 3D printed product by creating a manufacturing cycle consisting of the following repeating steps:

- Melt powder to produce layer and collect in process *DataPoints* like thermal emission
- Take picture of produced layer forming another *DataPoint*
- Analyze acquired *DataPoint* by the use of a model to generate new production parameters
- Save *DataPoints* to existing *DataTrace* of the product
- Apply new powder

Reiterating through this process will form a digital 3D representation of a 3D printed product forming the basis of a *DigitalShadow*. Similar sensor and data acquisition concepts which allow the evaluation of the process quality during USP ablation has been developed by Zuric et al. and allow for a similar production cycle during USP (Zuric et al. 2019). Figure 4.5 shows an example process for USP ablation. The plasma that is ignited during the process and is shown on the picture can be monitored spatially resolved in order to estimate the product quality. These digital shadows for process quality are typically designed for one specific manufacturing system from one individual vendor.

Especially in laser processing, these digital shadows could greatly benefit from a domain-wide usage not only limited in a vendor-specific ecosystem. However, in order to move one digital shadow from one machine to another one, it is vital to validate the data these DSs receive. We designed a microservice USP manufacturing system that allows the plug and play movement of DSs. In this system, every sensor and actor as well as analysis algorithm can be changed during execution and on demand, making it possible to reorder DSs running on the manufacturing system.

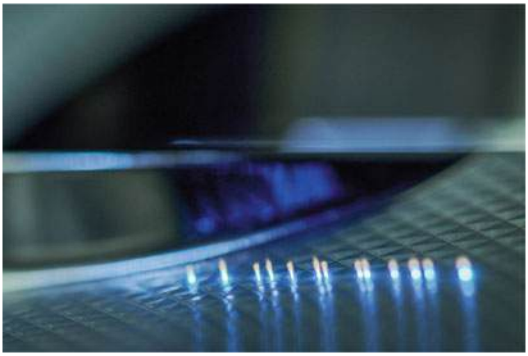

Fig. 4.5 Process emission in USP ablation can be monitored in order to form a 3D digital shadow of the produced product

However, changing from one vendor-specific sensor to another can have large influences on a digital shadow that analyzes this specific data trace. A single changed temperature sensor that sends temperature as integer values but now reads Fahrenheit instead of Celsius could lead to manufacturing errors or damages on the machine depending on the usage of the DS outcome. In order to minimize this effect of changed hardware setup, we proposed LISSU (Lipp et al. 2021), which allows the description of sensor produced data in order to validate digital shadows consuming these data streams. This bottom-up approach validates communication between two parties, e.g., a digital shadow and a actuator, before a communication takes place and verifies if both parties interpret the incoming value as Celsius. In case of a mismatch, either it converts the data or it disables the communication. By not only checking for syntactical correctness but also semantic correctness by the use of high-level semantic, configuration file errors can be reduced.

4.5.4 Automated Factory Planning

The task of factory planning is to design production systems that utilize their technological and organizational capabilities to process goods to deliver products to the customer. In today's dynamic market environment, changing requirements demand even for adaptable factories an increasing frequency of re-planning. In addition to reduced planning times, further cost pressure in the markets leads also to more complex and iterative planning tasks. To meet these challenges, the application of digital factory methods supports the planning process with design and simulation tools. However, heterogeneous sources of factory and planning information hinder a digital interconnectivity necessary to leverage the advantages of data-based and automated approaches (Schuh et al. 2011; Burggräf et al. 2021b).

To achieve interoperability of these data sources, future factory planning needs semantic information modeling as a foundation (Kádár et al. 2013; Büscher et al. 2016). An integrative information system forms the digital representation of the factory by combination of different factory *asset* data in its knowledge base, as shown in Fig. 4.6. The knowledge base contains general factory information in an *engineering model*, e.g., production quantities and machine dimensions, and *metadata* such as alternative configurations in planning scenarios. The semantic structure of this knowledge is set by a factory planning ontology as a conceptual model.

While the factory information system constitutes the basis for a digital factory twin, *DSs* offer an interface for machine-interpretable data exchange. For updated information, for example, by manual planning efforts, real-time updates from production feedback systems, or newly available asset data, a digital shadow imports the relevant Updadata as *data traces* into the information system. The semantically correct data integration is supported, because the DSs use the factory planning ontology as their *Model*. In another use case, implicit planning data is automatically checked with validation rules (Burggräf et al. 2021a) defined in the specific DS' *DataCalculation* model. The relevant factory information is queried

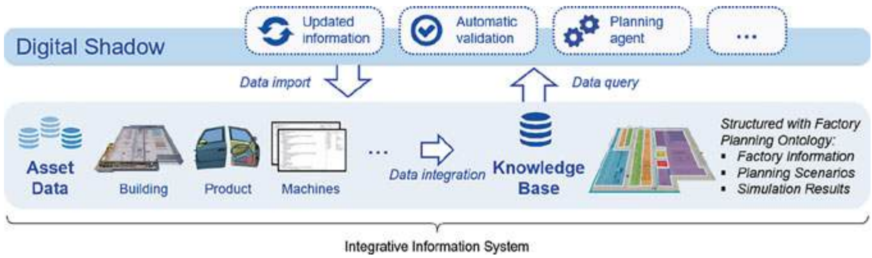

Fig. 4.6 DSs in factory planning allow for semantic information processing by linking to the ontology-based factory information system

from the information system. The third use case describes a planning agent that enables automated factory planning in specific planning tasks as its *Purpose*. An example is the calculation of machine utilization based on production quantities and resource capacities in the dimensioning of a production system. Here, the newly reasoned information, i.e., the machine utilization, is imported from its *Processing Source* to the knowledge base (Schäfer 2022). Conclusively, DSs in factory planning contain information that is specifically selected for use-case-specific context and requirements.

These use case examples demonstrate how digital shadows are essential to connect data sources for automated factory planning. Augmented by complementing the DSs with calculation models, semantic information modeling of relevant factory information offers digital decision support to planning experts. The presented concept of the factory information system will be extended to further use cases in the future.

4.6 A Method to Design Digital Shadows

A digital shadow aims to support the user in a decision-making process; thus, it needs to provide all relevant information to support informed decisions. Up to now, research lacks a method how to realize digital shadows with real data in practice. Based on our experiences from the four use cases in Sect. 4.5, we have developed a method that enables domain experts to describe digital shadows to the extent that software engineers or domain experts can realize them in software systems. The result of this requirements engineering process for a digital shadow is descriptions from the domain expert perspective, which are yet independent from the actual implementation.

To make an informed decision, we can use digital shadows. Such a decision is related to a problem, which has to be solved, data related to this problem and its relationships in *engineering models*, one or more solutions with *data calculation* and/or *simulation models* leading to them, and the goal and *purpose* of the solutions. These parts constitute a digital shadow (see Sect. 4.3).

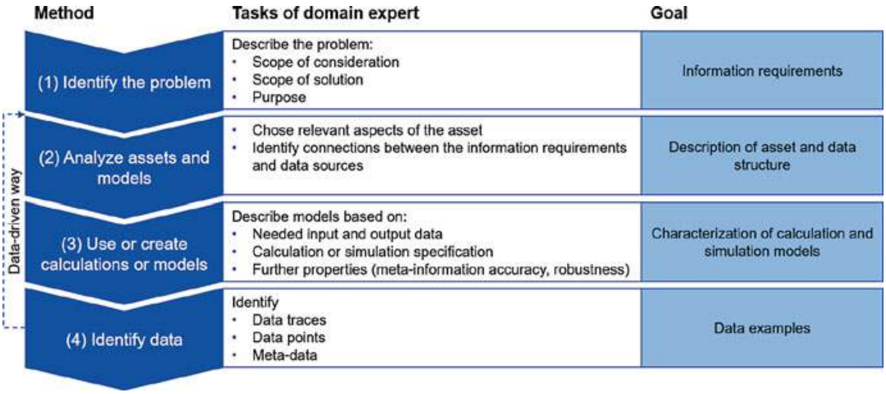

Fig. 4.7 The method to design digital shadows as domain expert

The following method can be applied by domain experts, e.g., product designers, factory planners, or production planners and controllers. Our method (see Fig. 4.7) includes the following steps: (1) Describe the problem, (2) analyze the *assets* and its *models* (3) use or build *data calculation* and *simulation models*, (4) identify needed *data traces*, *data points*, and *meta-data*. There are two ways to follow this method: from a domain expert and asset-centric perspective with steps 1–4 or in a data-driven way with step 4 before 2 and 3.

(1) Describe the problem In a first step, we identify a decision problem of the domain under consideration. The problem is described by the *scope of consideration*, the possible *solution scope*, as well as the *goal* of the decision, which is reflected in the *purpose* of the digital shadow.

The purpose specifies the goal of the digital shadow, and there exist different types of purposes, e.g., an improvement or optimization of objectives, or information about critical failures. The identified purpose serves as a basis for deriving the necessary information requirements. If the purpose is optimization of a specific process step, the user needs information about the objectives to be achieved and the necessary parameter adjustments. When it comes to identifying critical failures, the user needs information about the failures and its effects to prevent future failure occurrences. The user needs to define relevant assessment dimensions used to evaluate the solutions offered, e.g., logistical target values and costs.

(2) Analyze the asset and its models Each decision is related to one or more *assets* and the *models* and data available about them. As this data might be distributed among different systems and databases, models provide domain experts an abstract view on this data and allow them an easy selection of relevant aspects of the asset. By selecting relevant aspects from assets within existing models, the latter realization in software provides already a connection between the information requirements for a decision and the data sources.

(3) Use or creation of data calculation and simulation models To characterize a *data calculation* or *simulation model*, the domain expert must describe needed input data, the calculation or simulation specification, the output data, as well as further properties. The model's input data is described by the required data sets (attributes), data structure, and data quality. The calculation or simulation specification describes how the data should be aggregated, in which formulas should be taken for computation, or how the simulation steps should look like. How much can be specified here depends on the domain expert knowledge. The information output is characterized and described in terms of accuracy. The domain expert can provide additional properties as meta-information about the calculation or simulation specification, e.g., if the calculation should work online or offline, how accurate and precise the results need to be, and the requirements on interpretability and explainability, e.g., of machine learning models, as well as adaptability and robustness needs from the domain expert perspective.

(4) Identify needed data traces, data points, and meta-data In a next step, the domain users identify relevant *data traces* of the system including its *data points* and *metadata* by providing some examples. These examples can be used by domain experts to validate the input needed for data calculations and simulations. Specific data points at different aggregation levels might be required for each decision. Their aggregation has to be defined as data calculation in step (3).

When we apply this method to a specific use case, the result is a collection of requirements for the creation of the digital shadow. In the next step, we have to move from the requirements specification in the problem space to the solution space and the realization in a software system. Within that step, preparation might be needed, e.g., if data points were specified that do not exist in databases yet. Based on these specifications, e.g., the best fitting model can be selected, or a new model has to be created in cooperation with the domain expert. Implementation details have to be specified, e.g., the concrete locations of data, or if data type conversions are needed.

4.7 Data and Model Life Cycles in the IoP

Knowing better how to design digital shadows, the next step is to consider the impact of DS on the product life cycle. The data and models forming a digital shadow, e.g., from Sect. 4.5, can be used throughout the life cycle of a product, namely, *Development*, *Production*, and *Usage*.

Up to now, data and models tend to stay within these phases (see Fig. 4.8, left) and are often not even interconnected within each phase. Data is stored in data silos and not shared over the lifetime of a product (Brauner et al. 2022). To enable worldwide production labs, we have to extend the life cycle of data and model in various dimensions (see Fig. 4.8, right):

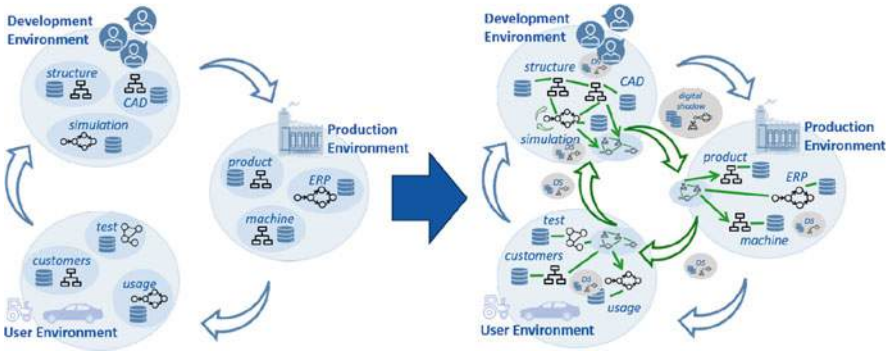

Fig. 4.8 Data and models within the product life cycle

1. *Sharing of data* can be realized by *using digital shadows*, which encapsulate relevant data parts, link them to models, and give the stakeholders full control over their sharing when realizing privacy-ensuring mechanisms.
2. *Models and data need to be connected* for more powerful analyses and real-time monitoring of processes. This can be realized in own models or ontologies or incorporated within a digital shadow.
3. *Models should be reusable* within the same phase, e.g., a simulation model for a product can be reused for similar products with specific parameters, or within the whole life cycle, e.g., the simulation model of one machine can be used in development and in the production environment to check the parameters to be.
4. *Models should be evolvable* over time such as the assets they represent, e.g., allow for additions or changes.

However, the creation of DSs within software systems utilizing models and data does have a life cycle as well: data acquisition, data calculation or simulation model formulation, integration, and adaptation. All of these phases place different requirements on the underlying infrastructure, which needs to be able to fulfill all these requirements in order to allow a hassle-free adaption of digital shadows.

During the *Data Acquisition* phase, the initial data trace is aggregated in order to build the foundation for a data calculation or simulation model. Depending on the purpose of the DS, the frequency of this aggregation can vary from a few data points per hour up to multiple GHz. Also the amount of used data traces varies. In a manufacturing planning scenario, it would make more sense to use multiple data traces with a relatively low data rate, while a production digital shadow, which could be used in laser processing or injection molding, typically requires less sensors but at higher data rates. Handling the sheer amount of data can be a challenge in itself and put high stress on the underlying infrastructure especially regarding persistent storage and bandwidth (Thombansen et al. 2021). The required skills in this phase typically involve domain-specific knowledge of the use case, knowledge of networking, and domain-specific APIs as well.

Afterward, during *data calculation or simulation formulation*, the acquired data is analyzed and used in order to produce a working DS. Some models like simulations and machine learning algorithms require large amounts of processing power in order to fulfill this step. Also the iterative design of such models can require large amounts of domain-specific knowledge as well as software engineering knowledge.

Integrating a digital shadow in running operations can become one of the largest challenges. They not only need access to the – sometimes live – data trace(s) in an efficient manner but also need the processing resources in order to fulfill its task. Depending on the workload the digital shadow meets, it might make sense to scale the DS up and down in order to adapt to incoming request changes. That is why we propose to run digital shadows that need this kind of scalability in a cloud data center or an on-prem edge data center. Another requirement comes from the vast amount of different digital shadows in a cooperation environment. Having an underlying organization and orchestration infrastructure that allows not only the scaling but also the discovery of deployed DSs is vital.

Production requirements change over time. Product portfolios are updated or discarded entirely, which leads to the last phase: *Adaptation*. Here, the digital shadow is modified if a change in the purpose of the DS is detected. This can lead to the deletion of data traces in order to save cost, updating models or scaling computing resources up and down depending on the need of the DS. Version control becomes a vital part of this scenario not only of the deployed models but of the whole digital shadow that needs to track all elements of the reference model.

These technical and domain requirements and the connections over different product life cycle phases show that a multidisciplinary approach is necessary to create worldwide production labs.

4.8 Outlook: Using Digital Shadows in Digital Twins

Digital shadows need software systems to manage them (Brecher et al. 2021); their initial setup, population with data, and deletion; and their evolvement, versioning, and sharing. Such functionalities can be integrated into one system or distributed among different services. One solution that could integrate these functionalities are digital twins (Kritzinger et al. 2018; Bibow et al. 2020). However, digital shadows can also exist without surrounding systems, if considered from the data sharing perspective and reduced purely to the aggregated data, metadata, and connected models. The original systems in the context of the IoP are CPPS or their subsystems (Feichtinger et al. 2022); however, further approaches discuss digital twins of organizations or humans. We distinguish three types of digital twins, whereby a DT can evolve across these three types: (1) "as-designed" digital twins exist during design (including technical design and simulation), (2) "as-manufactured" digital twins exist during construction, and (3) "as-operated" digital twins during runtime of a CPPS. In contrast to a digital shadow, the digital twin is able to influence the

CPPS (van der Aalst 2021), e.g., via self-adaptive functionalities (Bolender et al. 2021; Dalibor et al. 2020).

Digital twins can include different services using DSs, e.g., cockpits for visualization (Dalibor et al. 2020; Michael et al. 2022), process mining methods such as process discovery and prediction (Brockhoff et al. 2021; Bano et al. 2022), machine learning and AI methods (Liebenberg and Jarke 2020; Dröder et al. 2018), assistive services for human support (Michael 2022), supporting the assessment of sustainability targets (Fur et al. 2022), or services to compare DSs and their meta-information. Such services are implemented by oneself or integrated from a service catalog (see Sect. 4.4). We can support the setup of digital shadows within low-code platforms (Dalibor et al. 2022), and the digital twin could provide functionalities for versioning and evolution of digital shadows (see Sect. 4.7). Most of these concepts are not yet widely used in the industry, but our research within the IoP is trying to pave the way.

Moreover, we have identified a set of open challenges within two areas, which should be considered in the future: aspects to be realized for the applicability in worldwide production labs and challenges for improving the user experience when using and creating digital shadows and digital twins.

Challenges for the applicability in worldwide production labs These aspects need to be taken into account to ensure the usability of DSs within worldwide production labs for which different companies with multiple factories exchange data based on defined conditions.

- *Privacy concerns of data*: When handing over data, even it is only a restricted amount of it, the data provider wants to ensure that, e.g., the data is not used in another purpose than specified, stored longer than agreed on, or shared with third parties. Privacy policies allow data owners to control their privacy concerns and to monitor the compliance in supporting software systems. Thus, we have to incorporate relevant privacy concepts (Michael et al. 2019b) within the DSRM and define what components software systems such as the digital twin need to handle such digital shadow requests and related decisions (Michael et al. 2019a) while considering important privacy design patterns (Hoepman 2014) and the research of the International Data Spaces Initiative (Jarke 2020).
- *Selling digital shadows*: Given the shadow's purpose and the specification of the asset it works on, the digital shadow provides an interface for reusability. A DS, once designed and implemented, is itself a valuable property. It gathers new information in a smart and fast manner to fulfill its purpose. A company specialized in the remanufacturing and sale of this trade good could make use of this property. What then remains to be done is to precisely adapt the digital shadow to a new application. After a customer provided their asset specification, the communication interface needs to be implemented and models can be adapted to fulfill a slightly modified purpose. If the asset specification and purpose were enriched with semantic terms (see Sect. 4.4), this process could

even be automated using previous implementations. However, further research on business models and software services supporting the adaption is needed.

Challenges to be met for a user-friendly handling of digital shadows Designing DSs is a complex task and often requires close collaboration between domain experts and software engineers. We need to tackle these additional challenges to make digital shadow engineering as applicable as possible.

- *Reusable model repositories*: One of the key elements of our digital shadow is the usage of models to describe the asset's structure and behavior or to specify how the DS itself acts. Once specified, models describe a specific part of the DS and can be reused in other digital shadow designs as well. Having digital models in private or public repositories (see selling digital shadows) allows for an easy selection and creation of new composite models. To make this possible, all models need a semantic description of what it is supposed to stand for. In case of models meant for execution, such as calculation specifications or simulations, interfaces for input and output must be provided. These repositories of reusable models contribute to a user-friendly and domain expert understandable digital shadow engineering.
- *Automatic derivation of DSs from engineering models*: During design time, the system's structure and behavior are specified in engineering models. They describe in detail how the system is supposed to act and which parts of the system are of interest. We could use those engineering models to automatically generate digital shadows, e.g., we could generate the extraction of information of important system components from structure models or generate views on them (Gerasimov et al. 2021). When given 3D models, automatic behavior simulation could be possible. Nonetheless, all engineering models have to be set in context to the actual system and need to be enriched with their purpose information.

4.9 Conclusion

Within this chapter, we have presented the foundations of digital shadows: what concepts constitute them, their relations to ontologies, how to guide their creation from the domain-specific user perspective, and and how digital shadows can be integrated over different environments considering the product life cycle. We have further investigated four use cases and presented how digital shadows can support the challenges in these domains. Moreover, we give an outlook into what aspects have to be realized in software systems to create and manage digital shadows.

We envision worldwide production labs that foster cross-domain collaboration and are enhanced by sharing digital shadows that support decision-making, and we encourage DS reuse in other production scenarios. This requires for the different stakeholders to be able and willing to share data and models, and it requires from research to provide the needed concepts and technologies such as digital shadows and digital twins.

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Actionable Artificial Intelligence for the Future of Production

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Contents

Abstract

The Internet of Production (IoP) promises to be the answer to major challenges facing the Industrial Internet of Things (IIoT) and Industry 4.0. The lack of inter-company communication channels and standards, the need for heightened

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safety in Human Robot Collaboration (HRC) scenarios, and the opacity of data-driven decision support systems are only a few of the challenges we tackle in this chapter. We outline the communication and data exchange within the World Wide Lab (WWL) and autonomous agents that query the WWL which is built on the Digital Shadows (DS). We categorize our approaches into machine level, process level, and overarching principles. This chapter surveys the interdisciplinary work done in each category, presents different applications of the different approaches, and offers actionable items and guidelines for future work.The machine level handles the robots and machines used for production and their interactions with the human workers. It covers low-level robot control and optimization through gray-box models, task-specific motion planning, and optimization through reinforcement learning. In this level, we also examine quality assurance through nonintrusive real-time quality monitoring, defect recognition, and quality prediction. Work on this level also handles confidence, verification, and validation of re-configurable processes and reactive, modular, transparent process models. The process level handles the product life cycle, interoperability,

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and analysis and optimization of production processes, which is overall attained by analyzing process data and event logs to detect and eliminate bottlenecks and learn new process models. Moreover, this level presents a communication channel between human workers and processes by extracting and formalizing human knowledge into ontology and providing a decision support by reasoning over this information. Overarching principles present a toolbox of omnipresent approaches for data collection, analysis, augmentation, and management, as well as the visualization and explanation of black-box models.

5.1 Introduction

The digital transformation of production fundamentally reshapes the production landscape. The continuous and real-time exchange of data and information across all levels of the production process connects organizations within and across companies. Through this full integration of data across the whole life cycle of design, manufacturing, and use of products and across the whole value chains, production becomes more effective, efficient, and dynamic (Kagermann 2015; Liao et al. 2017; Brauner et al. 2022). Also, the diligent and efficient use of data opens up new business models and workplace opportunities for future generations (Becker et al. 2021b).

The Internet of Production (IoP) transfers the idea of the Internet of Things (IoT) to production and strives for the horizontal and vertical integration of production technology. It is thus related to similar concepts, such as Industry 4.0, the Industrial Internet (Bruner 2013), and the Industrial Internet of Things (IIoT) (Boyes et al. 2018). Yet, many approaches in this direction usually focus on one aspect at a time. They either focus on one layer of industrial environments, tackle challenges of a specific domain, or handle one perspective of the human stakeholders. In contrast, the IoP is a holistic approach to digital production and aims at achieving many of the visions of Industry 4.0 (Brauner et al. 2022; Pennekamp et al. 2019). It thus shares goals with several initiatives around the globe such as the industrial value chain initiative (https://iv-i.org/, last accessed: 2022-08-02), made in China 2025 (http://english.www.gov.cn/2016special/madeinchina2025/, last accessed: 2022-08-02), US advanced manufacturing initiative (https://www.nist.gov/document/molnar091211pdf, last accessed: 2022-08-02), and the high value manufacturing catapult (https://hvm.catapult.org.uk/, last accessed: 2022-08-02). But beyond that, the IoP builds on Digital Shadows (DS) and facilitates the idea of a World Wide Lab (WWL) (Brauner et al. 2022). DSs refer to fast, secure, task- and context-specific, purpose-driven, aggregated, multi-perspective, persistent, and multimodal views on data for production engineering applications (Liebenberg and Jarke 2020). The WWL enables the integration of data from experiments, manufacturing, and usage across lab, company, and country boundaries to generate insights.

The previous (► Chaps. 3, "A Digital Shadow Reference Model for Worldwide Production Labs" and ► 2, "Evolving the Digital Industrial Infrastructure for Production: Steps Taken and the Road Ahead") have laid the foundations for a secure, reliable, and trusted physical infrastructure of an IoP and motivated and defined the conceptual foundations of DS as the crucial nexus between the entities of the IoP. This chapter presents the functional perspective of the IoP and demonstrates how to make production data actionable, by linking mathematical models, Artificial Intelligence (AI), and Machine Learning (ML) with model-based analysis and control to provide actionable knowledge to either machines or decision-makers through trusted and bias-free humane interfaces (Calero Valdez et al. 2015; Pause et al. 2019).

The vision is the application of model-integrated AI which combines mathematical models, simulations, and data from different sources to create "data-to-knowledge pipelines." These pipelines transform massive data into insights and provide actionable knowledge to decision-makers. To this end, we define the following objectives:

1. Develop a systematic approach toward the combination of ML and model-based AI methods in context-adaptive production settings.
2. Develop visualizations, decision support systems, and human-centered interfaces that enable intuitive, adaptive, comprehensible, replicable, interactive assessments of model, simulation, and smart data at different scales and abstraction levels for reporting, diagnosis, prediction, and decision.
3. Definition of a systemic overview on data-to-knowledge pipelines in production and derivation of similarities between pipelines to enable the transfer and cross-learning between different pipelines.

A core idea is creating data-to-knowledge pipelines that transform raw machine data to actionable knowledge usable by either humans or machines. Actions can be taken by shop floor workers, supervisors, or managers. This knowledge can also be integrated into autonomous closed-loop control of the machine as well as other machines on the shop floor or production planning systems to realize self-adaptive production systems (Pause et al. 2019). These data-to-knowledge pipelines are the foundation of human-centered Decision Support Systems (DSSs) providing insights and enabling the human-in-the-loop to make informed, bias-free decisions (Brauner and Ziefle 2019).

Key drivers for the digital transformation in production are the need for process understanding and optimization, management decision support systems, workplace improvement through better ergonomics and safety, cost reduction through defect detection and time reduction, improved horizontal and vertical data integration, and better adoption to customer demands (Liere-Netheler et al. 2018).

Fisher et al. (2018) allow sharing and managing manufacturing capabilities in a micro-service architecture with a focus on inter-company integration (Siderska and Jadaan 2018). Our approach builds on the concepts of the World Wide Web and the

IoT to act as the IIoT. The IIoT promises many improvements in various industries through data exchange and integration, as well as the introduction of digital twins (Pennekamp et al. 2019). According to Xu et al. (2014), the IIoT aims to improve production processes by reducing energy consumption, increasing throughput, as well as safety and security, among other factors.

With the new wave of digitization of production and the increased use of sensors as well as retrofitting old machinery to fit the digitization initiative, Big Data (Manyika et al. 2011) is now omnipresent in production. To support collection, storage, and management of the vast amounts of data collected, the IoP introduced FactStack to manage the full data life cycle while maintaining the FAIR principles: that the data has to be findable, accessible, interoperable, and reusable (Wilkinson et al. 2016; Gleim et al. 2021a). We focus on both inter- and intra-company communication, as well as analysis and optimization of production processes on all levels of production. Our vision is to create, share, and use DSs in different industrial domains in a WWL.

This chapter serves as a toolbox that shows how to apply the concepts and methods of the IoP in different production domains and illustrate their added value. We survey our efforts to achieve the above objectives and demonstrate (1) the application of the concept of DSs in production systems, the creation of data-to-knowledge pipelines, and the realization of validated self-adaptive production systems. (2) Further we shed light on the realization of smart DSSs for human-in-the-loop and shorter, efficient, and agile innovation cycles that build on integrative and interdisciplinary methods. (3) Finally, we show methods for data-driven insights in production processes and back-coupling methods to transform these insights to actions.

This chapter covers the different layers in industrial environments (Fig. 5.1 illustrates its structure). First, we provide an introduction to the WWL and how autonomous agents can make use of DSs and date-to-knowledge pipelines in production (Sect. 5.2). Next, we address the creation and use of DSs at the machine level, where we address the work of individual machines (Sect. 5.3). Then, we address the process level that considers the relation between different production machines on a shop floor (Sect. 5.4). Additionally, we present overarching principles that provide support to the different AI methods as well as aggregate the different aspects toward the vision of the WWL (Sect. 5.5). The chapter concludes with a summary and brief outlook on the future of AI in production (Sect. 5.6).

5.2 Autonomous Agents Beyond Company Boundaries

To make the most out of AI applications in the IoP, particularly with the widespread use of Deep Learning (DL) techniques, we use DSs as an abstract digital representation of the different industrial processes. The digital shadows, inspired from database views (Liebenberg and Jarke 2020; Becker et al. 2021a; Brauner et al.

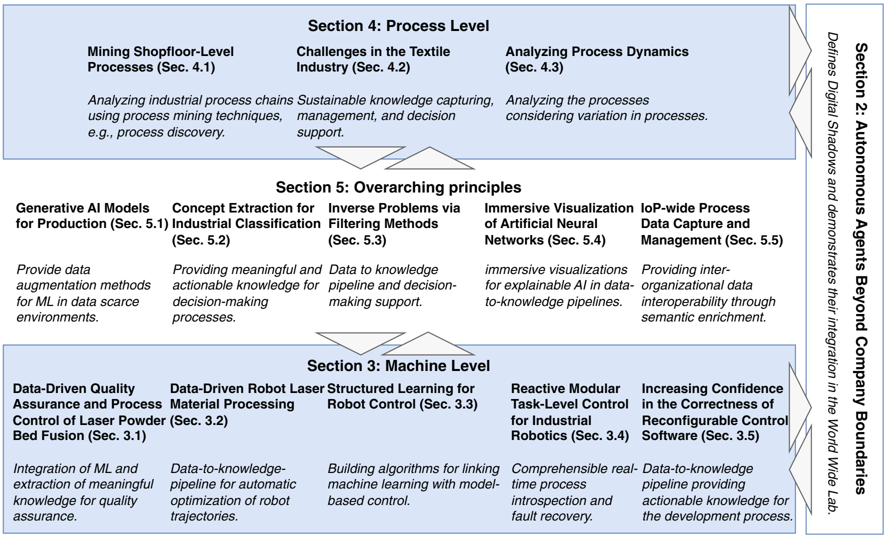


Fig. 5.1 Illustration of this chapter's structure and its individual approaches and contributions

2022), are used as an efficient alternative to digital twins (see previous ▶ Chaps. 3, "A Digital Shadow Reference Model for Worldwide Production Labs" and ▶ 2, "Evolving the Digital Industrial Infrastructure for Production: Steps Taken and the Road Ahead"). Mathematical models can be simplified or can be combined with measurement data or the knowledge created using the data-to-knowledge pipelines. One of the core ideas in the IoP is to share these digital shadows to support production processes with autonomous software agents we call WWL Agents.

The idea of the WWL Agents was introduced in Liebenberg (2021). These autonomous search agents push the boundaries of the IoP beyond control and optimization of production processes within a single company and allow sharing digital shadows across different companies enabling cross-domain data exchange. Additionally, a prototypical implementation of an infrastructure enabling this collaboration as well as two use cases from the IoP where WWL Agents are used to plan the processes of hot rolling and Fiber Reinforced Plastics (FRP) production was presented in Liebenberg (2021). The WWL Agents are able to generate and repair hot rolling schedules using a digital shadow of the process containing data and the fast mathematical models presented in Seuren et al. (2012). They are also able to use traditional planners such as the Temporal Fast Downward (TFD) planner (Eyerich et al. 2009) for the FRP use case.

Figure 5.2 shows the interaction between a production process which can share its digital shadow comprising of data and simplified mathematical models in the WWL. The digital shadow can then be used for automatic control and in DSSs.

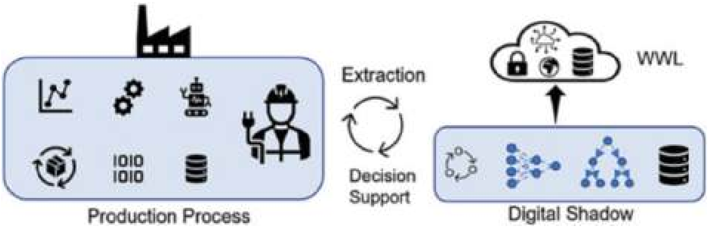


Fig. 5.2 A node in the WWL represents a production process whose models and/or data are continuously shared as a digital shadow in the WWL. These digital shadows are later used as a decision support system causing a feedback loop between the digital shadows and the process itself. (Image adapted from Liebenberg 2021)

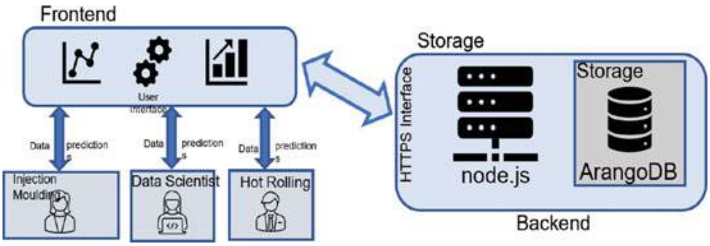


Fig. 5.3 An overview of the framework proposed in Liebenberg (2021) to support the WWL Agents in using the digital shadows provided by different nodes in the WWL. (©Image adapted from Liebenberg 2021)

Figure 5.3 shows an overview of the proposed architecture of the WWL. Users of different roles who provide different use cases have an interface that allows them not only to view process information such as quality prediction but also to upload digital shadows in the form of models and data. The interface acts as an entry point to the WWL as well as a decision support system that can provide insights to the human operators.

In the case of hot rolling, these insights can be in the form of a new rolling schedule or a corrected one in case the quality assessment model predicts an issue with the current one. The underlying models are DL models capable of making different predictions regarding the quality of the product fast enough to allow the operator to get the quality prediction and the suggested corrected schedule and then decide whether to apply the suggested changes in a matter of seconds.

In the case of the FRP manufacturing use case, the insights can be the actions to execute as well as resources and technologies to use in the different steps of the production scenarios. Since the digital shadow for this process contains a classical planner, the process expert would often need to share the problem description, including what resources and tools are available as well as the different steps to be executed for this product. This information is represented using the

Planning Domain Definition Language (PDDL), which is a widely used language for describing planning domains and problems (McDermott et al. 1998).

More use cases still need to be integrated into the framework presented in Liebenberg (2021) to have a truly global interface to the WWL which acts as a search engine with decision support powered by WWL Agents fulfilling the vision of Liebenberg and Jarke (2020). This would showcase the ability of these agents to act as a general cross-domain decision support system for use case experts and machine operators.

To this end, the following sections showcase the creation and usage of DSs for several use cases in the IoP: first for the machine level in Sect. 5.3 and then for the process level in Sect. 5.4. These DSs are extracted from different processes as analytical, DL, or generative models and can be shared across the WWL and later used by the autonomous agents of the WWL for process planning and plan repair, online and offline quality prediction, as well as decision support.

5.3 Machine Level

The aim of modern production is to increase its flexibility to satisfy quickly changing market needs and succeed at the fierce global competition. Therefore, it is crucial to create control systems for machines capable of quickly adapting to new tasks without much engineering effort. This section shows how novel control structures ranging from data-driven, over hybrid, to classical solutions, and their validation methods, can help boost the reconfigurability and flexibility of manufacturing systems on the example of four practical use cases. In the first use case, a monitoring system that enables data-driven control is presented for Laser Powder Bed Fusion (LPBF) machines. The second use case demonstrates the use of data-driven control systems for Laser Material Processing (LMP). The third and fourth use cases present the capabilities of hybrid control systems and hierarchical structures. They combine advantages of classical control methods with data-driven solutions. Finally, we discuss how the safety and robustness of complex control systems can be ensured via a new-generation monitoring architecture.

5.3.1 Data-Driven Quality Assurance and Process Control of Laser Powder Bed Fusion

Additive Manufacturing (AM) offers exciting new opportunities for manufacturing parts with complex geometries or small lot sizes. LPBF is a promising process for metallic components (Spierings et al. 2016). Using AM technique, high flexibility can be achieved when multiple parts with different geometries and sizes can be produced simultaneously. These lead to high freedom with low cost compared to conventional manufacturing. Due to the stochasticity of the manufacturing process, the LPBF process and its production quality are influenced by diverse factors such as laser parameters (Spears and Gold 2016), powder recoating system (Neef et al. 2014), particle gas emissions (Mohr 2019), or powder bed compaction (Ali et al. 2018). Unlike conventional manufacturing processes, the layer-wise production characteristics of LPBF offer the possibility of in situ monitoring and process control layer-wise, which provide insights during the manufacturing process by the monitoring data and adapt the laser scanning strategy for subsequent layers. Thus, it provides the possibility to investigate the correlation between in situ monitoring data and part quality of LPBF process. Based on this, a data-driven method can be used to characterize process performance. Detecting defects needs to be done as early as possible so that a control strategy can prevent the occurrence of the detected defect during the LPBF process. This way we can achieve “first-time-right” and high stability of product quality.

To reach this goal, a closed-loop control strategy to adapt the LPBF process to avoid and compensate defects on the printing parts is required. The whole strategy contains in situ monitoring data acquisition, product quality prediction, and closed-loop control development. The information provided by the in situ monitoring system is an insight into the LPBF process and the basis for a data-driven approach to process control. Existing monitoring systems can be categorized into on-axis and off-axis approaches (Imani et al. 2018). These systems give direct indications if something differs from a predefined “normal” processing condition, which potentially results in material discontinuity. But these anomalies cannot be classified or linked to precise defects yet. In practice, these anomalies are currently detected manually by process knowledge or by simple threshold methods based on monitoring images. According to study of Spears and Gold (2016), the generated amount of data for in-process monitoring or further data processing is a challenge that needs to be handled via careful data preparation. Furthermore, the data analysis approaches are applied for quality assurance. Existing applications are focusing on defect prediction within the product (Imani et al. 2018). These have shown the benefit of machine learning (ML) in a supervised manner. In practice, however, labeling monitoring data needs expensive measurement tools, e.g., computed tomography (CT), which is not applicable for all monitoring data. Thus, a semi-supervised or unsupervised method is required.

The overall approach of data-driven quality assurance can be divided into four steps as follows:

1. Monitoring system that captures layer-wise powder bed and radiation intensity images for LPBF to get insights into the process
2. Algorithms and expert know-how to detect and label anomalies on monitoring data
3. AI-based algorithms to recognize and classify defects
4. Closed-loop control strategy to avoid and compensate defects during manufacturing

In the first step, optical tomography and high-resolution powder bed camera systems are integrated into an EOS M290 LPBF machine. These will capture layer-wise radiation intensity during the manufacturing and layer-wise optical information before and after powder coating. Apart from that, these captured raw data require pre-processing steps such as calibration, noise reduction, and data alignment, to increase the quality for the further usage. Afterward, since these monitoring data cannot be labeled entirely using measurement tools, the labeling step is considered to be done in an unsupervised manner. The dimension of the acquired monitoring data is reduced by a pre-trained Auto Encoder (AE) and clustered by unsupervised learning methods according to the data point distribution. The clustered monitoring data is then evaluated by the process expert to reach the optimized label iteratively. The labeled data is used for process modeling in the third step to recognize and predict potential defects during the process. Finally, the novel control methods are developed and applied to optimize the product quality via parameter adaption during the process or via design optimization before manufacture.

We have integrated an Optical Tomography (OT) camera and a high-resolution powder bed camera on the LPBF machine EOS M290 as in situ monitoring systems for data generation. The monitoring data pipeline, which includes data acquisition, pre-processing (see Fig. 5.4), integration, and transfer, is implemented to generate data automatically during each print job. Based on the monitoring data of the OT and powder bed camera, the images are influenced highly by the environment, such as flare during the laser melting process and the illumination system inside the process chamber. With the original illumination system using LED strips on top, the powder bed image varied significantly depending on the location of the part due to light reflection on the exposed surface. This leads to a complicated situation in determining the typical profile of qualified printed parts. To reduce

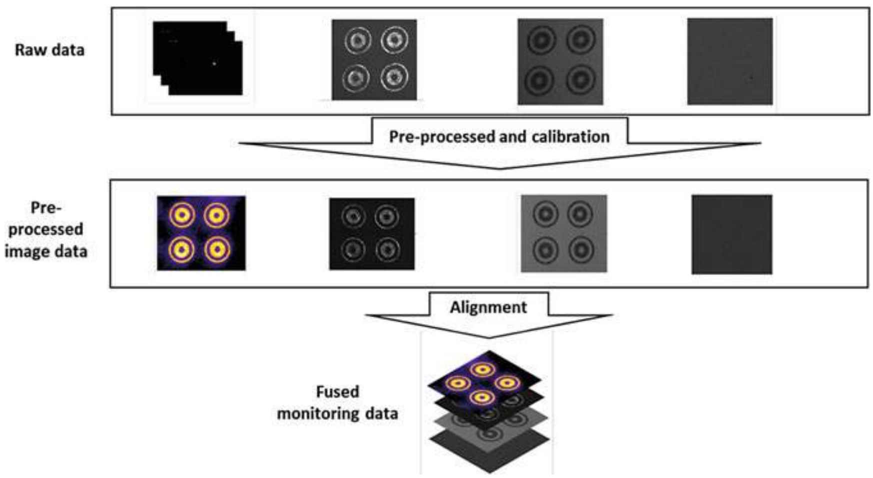


Fig. 5.4 Pre-processing of monitoring data from OT and optical camera for data processing

the environmental factors, an illumination system for powder bed camera using polarized light sources is designed and integrated into the LPBF machine. This shows the improvement of optical monitoring data by avoiding the reflection of ambient light. The printed areas in the optical monitoring images have high contrast to the powder areas, which reserve the morphology on the part surface. Furthermore, a DL-based network is designed to enhance the detailed features on the exposed surface of printed parts on the optical monitoring data (Zhang et al. 2022), which has shown the benefit to provide more information to data labeling.

In the next steps, high-quality monitoring data is required to remove irrelevant features and environmental noise to achieve highly robust data labeling. Data-driven algorithms and expert knowledge should be used to detect anomalies in the LPBF process and classify them as defects. In addition, knowledge of these defects must be discussed individually to determine if it is possible to prevent or to compensate them. At the end, these will represent a control strategy to maintain a high-quality product. This strategy will be integrated into the LPBF machine to evaluate and demonstrate the gains in actual performance. This will enable the use of "data-to-knowledge pipelines" in AM to increase the product quality by extracting process knowledge out of monitoring data to control the manufacturing process.

5.3.2 Data-Driven Robot Laser Material Processing

LMP is characterized by process variety, high accuracy, and geometric flexibility (Helmut Huegel 2009, p. 6). Furthermore, LMP is contact-free which means that no restoring forces act on the kinematic structure of the robot (Helmut Huegel 2009, p. 174). This, in comparison to conventional processes like milling (Cen et al. 2016; Wang et al. 2009), makes it possible to use an Industrial Robot (IR) for LMP. Compared to commonly used machine tools, IRs offer higher geometric flexibility and a bigger workspace at lower costs and hence emphasize LMP's advantages. Nevertheless, low stiffness of the serial kinematic configuration still causes position inaccuracies of the Tool Center Point (TCP) during motion along a given tool path. This leads to lower overall process quality in laser processes, e.g., laser material deposition (Bremer et al. 2021).

Minimization of attained tool path deviations for a steadier motion through laser-specific and model-based trajectory planning can be a promising approach to enable low payload IR for more precise motion and hence higher-quality LMP. Thus, model-based trajectory planning and optimization of motion are investigated using a task-specific digital shadow.

In this context, different optimization criteria such as jerk minimization can be used to generate more suitable robot trajectories and increase trajectory accuracy (Dai et al. 2020). Furthermore, dynamic models of robots are enhanced with measurement data of the robot state to enable better trajectory planning and control and thus enhancing the digital shadow the models are based on. This holds the possibility for further customization and trajectory optimization with a scope of, e.g., minimal energy consumption (Boscariol et al. 2020).

From robotized LMP processes, specimen, process, and robot data can be gathered. The goal is to use specific data from robot and process states to build models of the robotic system and the process induced kinematic degrees of freedom. Based on this data-driven optimization algorithms such as Reinforcement Learning (RL) or graph-based optimization are employed to generate motion trajectories. Afterward, in situ measurements of the robot state during the process are fed back into the models created as described above to further optimize trajectories.

Our approach to LMP-specific trajectory planning is split into two steps. The first step requires an accurate model of robot dynamics. To model the process degrees of freedom, conventional approaches (Sicilliano et al. 2010, p. 247f) are extended with LMP-specific virtual joints – which requires large amounts of expert knowledge. Additionally, Recurrent Neural Network (RNN)-based models making use of data-to-knowledge approaches are evaluated in comparison (Ogunmolu et al. 2016). Novel TCP position estimation concepts are tested regarding their ability to generate a tool for data gathering and dynamic model validation. Model-based inverse kinematics under LMP-specific restrictions are computed for trajectory planning, thereby generating one initial solution of the inverse kinematics problem. The second step makes use of the initial inverse kinematics solution to further minimize trajectory deviation.

Conventional – e.g., graph-based – trajectory optimization approaches are compared to RL-based trajectory optimization approaches. RL-based trajectory optimization approaches are trained both in silico – in a simulation – and in situ, on the real, physical robot. Loss functions of both optimization approaches focus on, e.g., jerk minimization to force smooth trajectories or on end-to-end attained tool path deviation minimization. All approaches make use of LMP-specific restrictions and redundancies, such as required constant TCP velocity and redundancy due to, e.g., a rotational symmetric tool: the laser beam.

Using the described tools, different low payload IRs can be enabled for LMP in production environments with lot size one and highly individualized products by lowering hurdles for task-specific implementations. In combination with suitable sensor concepts for state estimation, IR state data for our approaches is dynamically captured. Based on previous work, the influence of further optimization parameters such as jerk minimization or minimal overall energy consumption of robot motion must be investigated to determine suitable optimization strategies. More research must be conducted on how these principles can be employed for RL-based trajectory planning to assess the overall capabilities.

5.3.3 Structured Learning for Robot Control

Machining of medium- and large-size components (e.g., for the aviation industry) is almost exclusively conducted on machine tools. These machines possess a smaller workspace than their installation space and are more expensive than conventional IR, for instance. IR are less rigid, which negatively impacts the workpiece quality. A model-based feedforward control can compensate the low rigidity of the robot.

For this purpose, an analytical or data-driven model of the robot dynamics is used to calculate a compensation torque from given variables of the robot joints. Analytical dynamics models are based on physics equations such as the Newton-Euler equations, used to describe rigid-body dynamics. These equations depend on inertial parameters, which must be elaborately identified for each robot type. Furthermore, analytical models are error-prone, since it is difficult to embed complex nonlinear effects such as friction. Data-driven models, such as neural networks, on the other hand, try to find relationships between the input and output data of a specific system. They are able to model complex nonlinearities (given sufficient data), but without explicit knowledge about the physical behavior of the system.

Structured learning aims to combine the advantages of these approaches by incorporating available structural knowledge (e.g., in the form of physics priors) into data-driven models (Geist and Trimpe 2020). The resulting model predictions are supposed to comply with critical system constraints under improved generalization (capability to adapt to new, unseen data) and data efficiency. Current approaches of structured models for learning dynamical systems are, for example, deep Lagrangian networks (Lutter et al. 2019) and Lagrangian neural networks (Cranmer et al. 2020). Nevertheless, these models neglect friction effects and show deficits regarding prediction performance and generalizability.

The objective of our work is to extend the Newton-Euler equations with neural networks, therefore creating a structured neural network, to accurately model the dynamics of an industrial robot. Assuming that the major prediction errors of the Newton-Euler equations result from friction and elasticities of the robot joints, it is reasonable to model these specific effects with neural networks (see Fig. 5.5). To avoid overfitting and increase generalization, it is suggested to simultaneously train the inertial and network parameters of the analytical model and the neural network. The training process is accelerated by eventually reaching a local optimum. Therefore, an exact estimation of either set of parameters is averted, which leads to a better prediction for data points outside the training realm.

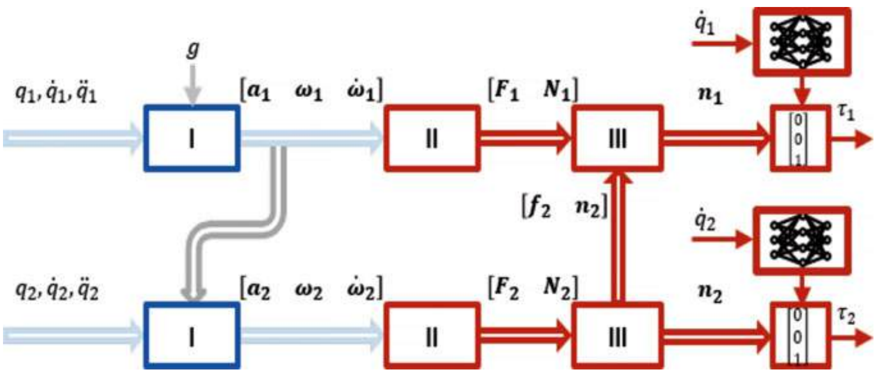


Fig. 5.5 Concept of a structured neural network for dynamics modeling of a robot with two degrees of freedom using the Newton-Euler equations and neural networks

The first findings show an increased interpretability of the structured neural network due to the integrated Newton-Euler equations. Furthermore, the neural network is able to model the characteristic friction behavior during transitioning between negative and positive velocities. Nevertheless, simultaneous training of the inertia and the network parameters is complex without setting individual learning rates and the model accuracy needs to be optimized as well.

Using this new type of structured neural network for model-based feedforward control can prepare industrial robots for highly dynamic processes, like machining. By increasing the interpretability of the network, it may be more suitable for use in a production environment compared to a black-box network because of improved worker acceptance and trust. Further research must be conducted regarding prediction performance and generalizability as well as field studies on real robot applications.

5.3.4 Reactive Modular Task-Level Control for Industrial Robotics

Use cases of robotics go beyond the full automation seen in machining, additive manufacturing, and multi-robot assembly, to Human Robot Interaction (HRI) tasks, which include human-robot teams in collaborative assembly and robot teleoperation in metal forming (Baier et al. 2022). In such tasks, it is important to decrease the reliance on DL for robot control and turn to a new paradigm of robot programming.

To handle the different requirements and cover all use cases in the IoP, we propose extending Behavior Trees (BTs) for the task-level control of these robots. BTs offer a modular alternative to traditional task-level control methods such as Hirarichal Task Networks (HTNs) or Finite State Machines (FSMs) (Colledanchise and Ögren 2018; Iovino et al. 2020).

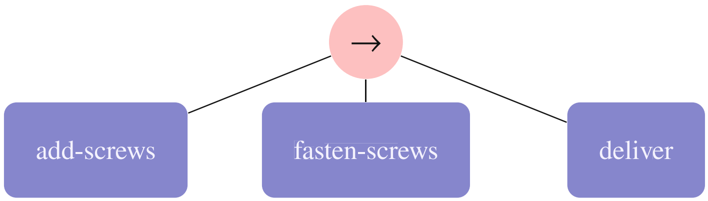
A Behavior Tree (BT) is a model that represents a robot's behavior in a tree structure. The tree is started by ticking the root node. Each tick is a signal that starts at the root to begin the tree execution and then is propagated to the children till it reaches the leaves. When a node is ticked, it returns a status $S \in \{\mathcal{S}, \mathcal{R}, \mathcal{F}\}$ representing Success, Running, or Failure, respectively, to its parent indicating its current state. As defined in Colledanchise and Ögren (2018), each node has one of two types: execution and control flow. Execution nodes are leaf nodes and are responsible for direct interaction with the world. They are either condition nodes, which check certain conditions, or action nodes, which execute actions. Control flow nodes make decisions regarding the propagation of the ticks to their children (Colledanchise and Ögren 2018) as follows:

- Sequence nodes: tick their children in order. Whenever a child fails, they return $\mathcal{F}$, $\mathcal{S}$ if all children succeed, or $\mathcal{R}$ otherwise.
- Selector nodes: tick their children in order whenever a child returns $\mathcal{R}$ or $\mathcal{S}$ they return the same!. If a child returns $\mathcal{F}$, they tick the next. If all of them fail, the selector node returns $\mathcal{F}$.

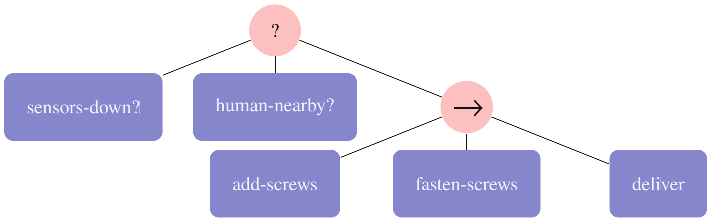
- Parallel nodes: tick the children in parallel. They return $\mathcal{S}$ if at least m children return $\mathcal{S}$, $\mathcal{F}$ if $N - m + 1$ children fail, and $\mathcal{R}$ otherwise, where m is a parameter of the node and N is the number of children.
- Decorator nodes: have only one child and can be used to implement custom policies modifying the returned status of the child.

The tree structure, combined with the returned status, increases the modularity of BTs compared to other robot programming approaches. Additionally, the ticking mechanism increases the reactivity. For example, in the assembly task seen in Fig. 5.6, a safety branch can be added to a tree without modifying the core task. Moreover, if we need to execute the task using a different robot, we only need to reprogram the leaf nodes. We are also able to examine the state of the robot at runtime and find if any problems were faced. This aids in online decision-making to avoid product defects or quality issues. Additionally, some approaches are able to further exploit the reactivity and modularity of the tree by evolving it during runtime to overcome any unforeseen problems (Colledanchise et al. 2019).

We extend the set of BT node classes with new node types that aid in the HRI tasks. We propose $\mathcal{H}$-nodes allowing the robot and human teammates to hand over workpieces seamlessly while minimizing the idle time that may arise when the robot is waiting for the human to finish a sub-task (Behery et al. 2021). This is done by enhancing BTs with an expert system (e.g., CLIPS (Wygant 1989)) that allows the



(a) The main tree for a part of a desk lamp assembly task. This includes adding the screws then fastening them, and finally deliver the lamp.



(b) The tree for assembling a desk lamp after adding sensor and human proximity checks.

Fig. 5.6 An example of a BT used to assemble a desk lamp. (**a**) shows the core of the assembly task, while (**b**) shows the assembly task as the child of a Selector node (root). This tree only executes the assembly if the sensors of the robot are up (first branch fails) and that there is no humans nearby (second branch fails). (**a**) The main tree for a part of a desk lamp assembly task. This includes adding the screws, then fastening them, and finally delivering the lamp. (**b**) The tree for assembling a desk lamp after adding sensor and human proximity checks robot to reason about the human's sub-task and make decisions on when to pause or resume execution of the tree based on the outcome. This extension allows us to form tasks that treat the robot and human teammates as two agents with different capabilities. This way, we can exploit a robot's precision and repeatability while making use of human dexterity and flexibility for handling deformable objects (e.g., cables, cloths, . . .).

To handle teleoperation tasks, Behery et al. (2020) present a method to discretize a robot operator's commands to adapt them for discrete control systems like a BT. This is achieved by applying hysteresis thresholding used in the Canny edge detector (Canny 1986) on the input signals to detect shifts in the operator's commands indicating a change of action. This approach allows us to switch from continuous user input to discrete actions, such that we can learn and encode patterns of operator behavior. These results are a step toward extracting insight from the operator input data. They allow us to use BTs as a representation of the operator patterns despite the traditional use of BTs for discrete behavior modeling.

The future work planned in the IoP regarding task-level action execution and monitoring is to further augment BTs with new node classes that increase their reactivity and guarantee an optimal execution while maintaining modularity, readability, and ease of development.

5.3.5 Increasing Confidence in the Correctness of Reconfigurable Control Software

The IoP severely disrupts the Cyber-Physical Production System (CPPS) life cycles and value chains (Jeschke et al. 2017; Pennekamp et al. 2019). The data-driven approach and the increased reconfigurability and flexibility of the CPPS blur the distinction between development and operational phases along the life cycle, resulting in shorter and more frequent production cycles.

The heterogeneity increases through service-oriented architectures, leading to emergent behavior often unforeseeable during the development phase. Therefore, the verification and testing of logic control software have to go beyond traditional validation of predefined properties to meet intrinsically and extrinsically changing requirements (Grochowski et al. 2019a).

As safety and robustness are vital properties of CPPS, many approaches emerged tackling the diverse and complex field of verification and testing on different levels (Grochowski et al. 2020). Given the intractability of exhaustively verifying distributed, ad hoc CPPSs, configurable runtime monitoring and passive testing are a compromise between feasibility and expressiveness. Runtime monitoring is a lightweight technique that bridges the gap between testing and verification and helps increasing the confidence in the correctness of the digitally networked factory (Grochowski et al. 2019a). Paired with passive testing, a specification-based black-box technique, software quality assurance can be performed during the operational phase of the CPPS to a certain degree (Grochowski et al. 2019b). As reconfigurability and ad hoc networking lead to emergent behavior, passive testing and runtime monitoring are used to safeguard the functionality of the CPPS during the operational phase. Typically, the constraints imposed by safety-critical components in a CPPS contradict the characteristics of most runtime monitoring techniques, which rely on additional source code annotation or instrumentation found in the literature (Cassar et al. 2017). External runtime monitoring is a nonintrusive technique easily embeddable into a system of communicating components. It connects via the underlying machine-to-machine communication protocol of the service-oriented architecture as an additional service, can run on existing or additional hardware, and is scalable. A benefit of the physical separation of the runtime monitor and the monitored component is the guarantee of no delays or restrictions due to the monitoring functionality. Figure 5.7 depicts a high-level overview of an exemplary architecture embedding the monitoring services using an adapter. Because the runtime monitor and passive testing rely on meaningful information exchanged between the services to claim the properties of interest about their internal behavior, the adapter serves as a semiformal interface between the services of the CPPS and the monitoring services. The adapter is responsible for transforming the messages passed between the services into a suitable representation for analysis. The runtime monitor checks the transformed execution trace against a set of formalized requirements and communicates the results back to the adapter, further distributing the results to a database or human experts. Whereas the runtime monitor guarantees that the requirements are not violated, the passive tester monitors the conformance between the implementation and the specification during execution. Due to task-specific digital shadows consisting of temporal data traces or their aggregation and abstraction, it is possible to monitor and test properties beyond the observable behavior, hence partially alleviating the drawback of not annotating or instrumenting the components (Bibow et al. 2020; Jarke et al. 2018).

We implemented a nonintrusive runtime monitoring algorithm as a rudimentary fail-safe. This forces the CPPS to halt in case of a violation of a monitored requirement (Grochowski et al. 2019a). Additional requirements that should be monitored due to intrinsic or extrinsic changes can be added on the fly during the operational phase. The runtime monitor is connected via a semiformal interface to the MQTT's message broker and subscribed to all required topics for the verification task. The runtime monitoring algorithm expects requirements to be expressed formally, e.g., in Metric Temporal Logic (MTL) (Thati and Roşu 2005). A set of requirements templates has been derived from the formal requirements to lower the complexity inherent in generating runtime monitoring objects. Even though the runtime monitor is capable of reasoning about the future time fragment of MTL, we limit ourselves to the past fragment due to inaccuracies caused by asynchronous communication. For

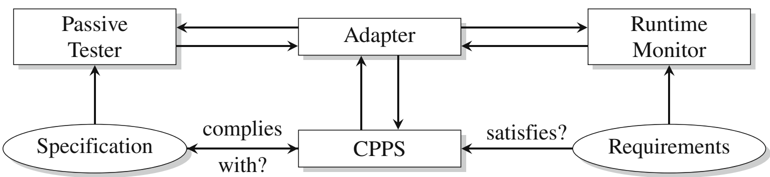


Fig. 5.7 High-level overview of the monitoring architecture

each formalized requirement in MTL, the runtime monitor creates and maintains a monitoring object. Once an observation arrives at the adapter, it notifies each monitoring object subscribed to this particular observation, updating its respective internal state. If enough observations have been considered or a time-bound has expired, the formalized requirement can be evaluated conclusively, and the monitoring object can obtain a verdict. Aside from notifying the runtime monitor, the adapter also notifies the passive tester once a new observation arrives (Grochowski et al. 2019b). As the specification of the CPPS is modeled as a program graph, the passive tester receives either an input action with parameters or an output action with the corresponding digital shadow from the adapter. The simulation starts from the initial state in the transition system described by the program graph of the specification and mimics the observed behavior until an artificial sink state is reached, which indicates deviating behavior. In that case, the passive tester stops and saves the deviating execution fragment for further analysis. It then tries to backtrack to the last location in the graph where the specification and the CPPS were conforming. From that point on, arbitrary behavior is logged until the initial location is reached again. This is justified by the fact that in case a severe violation occurs, it is detected by the accompanying runtime monitor, which would put the CPPS into a safe state or halt. Since the execution of a CPPS usually exhibits cyclical behavior, the passive tester and the CPPS are resynchronized in their initial locations, and the simulation can start over. The prior saved deviating execution fragments can be, on the one hand, used to investigate whether the underlying program graph of the passive tester was underspecified and, on the other hand, aid and guide the developer during the testing and debugging process after reconfiguring the CPPS.

To evaluate the proposed architecture in an industrial setting, the techniques were integrated into an industrial-like use case. We used a service-oriented architecture employing the concepts of digital shadows, edge computing, and their interconnection to realize a completion task of a windshield manufacturer (Brecher et al. 2018, 2019). Here, we were able to monitor the predefined properties during the operational phase, and the passive tester detected deviations from the behavior of the CPPS at runtime. The deviations are limited to implementation inaccuracies with regard to the specification and hence do not reflect any severe errors; the CPPS still produced a feasible outcome, i.e., a completed windshield, but it did not adhere to the expected behavior. While runtime monitoring is a possible solution to monitor requirements in distributed and ad hoc production networks as above, it does not comply with industrial standard communication cycles down to a few milliseconds. Therefore, it is suboptimal for checking requirements regarding the process control, but it can provide insights into the observations in retrospect.

In conclusion, runtime monitoring aids in claiming non-real-time critical propositions over the observable behavior of the CPPS (Grochowski et al. 2019a). Furthermore, it was shown that a specification-based, passive, black-box testing approach paired with runtime monitoring is a suitable technique for increasing the confidence in the correctness of the CPPS during the operational phase. Nevertheless, the application of both approaches is severely limited in the expressiveness with regard to parallelism, asynchronous behavior, and underspecification of the CPPS. Moreover, the derivation of a passive tester from the specification modeled in SysML (Systems Modeling Language) is currently a manual, tedious, and error-prone task that has to be repeated with every change in the component's software. In conclusion, this renders the passive tester far from being a push-button technique (Grochowski et al. 2019b).

We presented a non-collaborative production task in which increasing the confidence in the correctness of the manufacturing process results in limiting the damage or harm being done to the production plant or the manufactured product. Other promising use cases are collaborative production tasks. Here, behavior trees can model human-robot collaboration, because they are suitable for describing and visualizing the potentially complex behavior of autonomous agents (Colledanchise and Ögren 2018). Current approaches for verifying such behavior trees are semi-automatic and require low-level details about the behavior of actions. Therefore, future work should investigate safeguarding for production tasks involving human-robot collaboration by modular verification of reconfigurable behavior trees.

While this chapter focuses on techniques for problem-solving at the machine level, adequate methods for solving emerging problems in a digitally networked factory require contemplation across all levels. The next chapter focuses on issues and insights into potential solutions regarding the process level's perspective.

5.4 Process Level

Implementing data-to-knowledge pipelines that generate insights into entire processes requires expanding the scope from the machine to the shop floor and, eventually, the company level (e.g., including supply chains and multiple factories (Pause et al. 2019)). This, however, raises new challenges regarding data provenance, production planning, or the creation of holistic integrated views on the process. These challenges are further amplified by a constantly increasing complexity of assembly processes. For example, while traditionally special purpose machine manufacturing is characterized by complex and versatile assembly processes, increasing product complexities and customization demands lead to generally more versatile assembly processes. At the same time, companies collect increasing amounts of data on their processes. On the shop floor level, such data are often in the form of discrete event data. Events are, for example, recorded when an assembly step is completed and can contain additional information such as the important machine parameters. Each event is endowed with a timestamp and multiple events are related to (at least) one case (e.g., a product/material id).

Within the IoP, we are following two main tracks to generate insights and improve shop floor-level processes. On the one hand, we apply and conduct research on process mining techniques that leverage the discrete event data. Process mining is a new field of data science that investigates the behavior of processes based on discrete event data (van der Aalst 2016). We investigate how data-driven approaches can be complemented by additional manufacturing-specific structural information to generate comprehensive views onto shop floor processes. Moreover, we develop methods that reveal problems in manufacturing processes (e.g., by monitoring changes). On the other hand, we examine how expert knowledge can be extracted, documented, and exploited in traditional craftsmanship like the textile industry by employing the concepts of the IoP (e.g., AI, ontologies).

5.4.1 Mining Shop Floor-Level Processes

A major challenge when analyzing shop floor-level processes is to create a holistic view on the process. Even though process mining is concerned with the analysis of end-to-end processes, existing techniques are often insufficient to tame the complexity of manufacturing processes. In particular, automatic process model discovery usually fails to return understandable and meaningful results if we have many concurrent processes. However, in contrast to other business processes, additional and reliable structural information is frequently available for manufacturing processes. In this regard, we particularly distinguish between structural information on the shop floor (i.e., how machines or assembly steps are connected) and information on the material composition (e.g., bill of materials).

Assembly Model Information A common approach to organize the shopfloor is to structure the individual assembly activities into assembly lines. This – machine- or assembly activity-centric – production organization can often be directly translated into process models. In particular, for structured but semiautomated production processes for which human resources serve as an essential part of the production processes, process mining can point out the challenges in terms of discovering performance and compliance problems. In such processes, friction may particularly occur at the intersections of different subprocesses (e.g., the assembly cannot proceed due to missing subparts). Therefore, a holistic overview over the production is important to identify problems and eventually improve the process. In the use case of e.GO Mobile AG (Uysal et al. 2020), a young manufacturer of cost-effective and customer-oriented electric vehicles, we modeled the manufacturing process, comprising a general assembly line and several associated subassembly lines, by means of a process model. For the analysis, we applied the PM^2 process mining project methodology (van Eck et al. 2015) and analyzed the process execution in the production line. An interesting finding is presented in Fig. 5.8 which visualizes

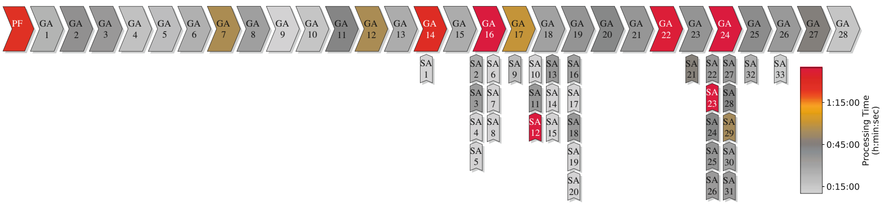


Fig. 5.8 Visualization of service time (red color scale) on the general assembly line and subassembly stations. The major bottleneck in the process is formed by the general assembly station GA16

the service times of the stations which are colored in a gray-orange-red color scale. Here, we can easily observe that certain stations expose a bottleneck, such as station *GA 16*, which are associated with sublines, causing some delays in the manufacturing process.

Material Composition Models A different approach to model the production follows a material-centric view by means of material composition models, which describe how different materials (e.g., subparts of a product) are related to each other. For example, the assembly is structured by means of **M**ulti-level **M**anufacturing **B**ills **o**f **M**aterials (M^2BOM). The provided information on the subcomponent composition allows to draw conclusions on the assembly order that are usually reliable due to physical constraints (e.g., supercomponents cannot be finalized without the corresponding subcomponents). Therefore, this information can be exploited to discover well-fitting comprehensive assembly process models.

Within the IoP, we proposed an analysis framework that incorporates additional structural information – particularly M^2BOMs – to analyze manufacturing processes presented in a use case study of Heidelberger Druckmaschinen AG (Brockhoff et al. 2021). In this framework, we discover an M^2BOM-based performance-aware assembly model that, in the first step, is used to discover potential bottlenecks. By incorporating additional manufacturing-specific information, we tame some of the complexity of assembly processes and visualize them beyond small excerpts. In the second step, we apply performance-oriented process mining techniques to further analyze bottleneck candidates to identify root causes.

5.4.2 Challenges in the Textile Industry

In Germany, the textile industry is predominantly formed by Small and Medium sized Enterprises (SME) and is one of the sectors in which large parts of the work steps are still manual (Brillowski et al. 2021b). This includes not only physical work steps but also the planning, design, and layout of processes.

Especially in the field of FRP, the planning of the manufacturing processes is challenging. FRP consist of a limp textile and a liquid plastic matrix. During the multistep process, a highly rigid, solid lightweight composite is created with the help of various technologies (Soutis 2005). Due to the different, changing aggregate states of the material, existing planning and decision support systems cannot be transferred without time-consuming adaptation. In addition, the planning for each novel component must be started anew due to geometric complexity, fiber orientations, and application requirements.

In the course of planning, various decisions have to be made regarding the material (e.g., glass or carbon? 200 g/m^2 or 450 g/m^2 grammage?), the technologies (e.g., CNC cutter or ultrasonic knife for cutting textiles), and the sequence of the process steps (e.g., A before B or A, B, C in parallel). In this context, a labor-intensive and intuitive trial and error procedure based on experience has become established in industry, resulting in promising technology alternatives being overlooked (Brillowski et al. 2020, 2021b).

In this regard, AI approaches promise automated and objective support in decision-making. However, the acceptance and use of these approaches within the textile industry are low, partly because the textile industry is more conservative due to inaccuracies in prediction and fear of substitution (Jacovi et al. 2021). To increase the efficiency and reproducibility of planning FRP process chains, we developed a user-centered planning tool with an integrated decision support system based on human-centered AI (Schemmer et al. 2020). In the form of a wizard, process planners can sequentially define the various steps of a process chain in FRP manufacturing by selecting the required activities (e.g., cutting, fixating, etc.).

When the sequence is finalized, a recommendation system presents suitable technology and parameter suggestions for each process step. The suggestions are based on historical data and provide global and local feedback on the process chain. The decision-making authority remains with the worker and they decide whether to accept or reject suggestions. As global feedback on the recommendation, the estimated costs, quality, and production time for products made in this process chain is presented (see left side of Fig. 5.9). Further, the planning tool displays local feedback by indicating possible complications at individual process steps, which can be fixed by choosing a different activity if necessary (see right side of Fig. 5.9).

In a study, users articulated both advantages and disadvantages of the planning tool: Apart from the criticism of fixed parameters, the application was particularly convincing due to the large number of different and transparent suggestions that a decision-maker can reject or accept (Brillowski et al. 2022a). In a further evaluation with domain experts, we benchmarked the user-centered tool against other tools in terms of planning effectiveness and efficiency, but also subjective measures such as trust, usability, and experience of autonomy. The tool was attested a high usability (91.8 System Usability Scale (SUS) score) and user acceptance (Brillowski et al. 2022a). However, the study also revealed that the comprehensibility of proposed alternatives is one of the critical aspects that significantly influence the subsequent user acceptance. In this context, the research field of eXplainable Artificial Intelli-

Fig. 5.9 Illustration of a recommended process configuration from the FRP process chain planning tool with a global evaluation of the whole chain on the left and local information on possible problems on the right

gence (XAI) offers a variety of possibilities to understand algorithmic decisions and, for example, to obtain reasoning for the exclusion of alternatives (Brillowski et al. 2021a). Besides the need for improved transparency, AI-based decision support systems require large amount of data to make meaningful suggestions. Yet, within and beyond the textile industry data is often only insufficiently or not at all available (Brillowski et al. 2021c). We explore different approaches to address the data scarcity dilemma.

First, the available data sets can be used more efficiently through augmentation or different learning approaches. We are already using Generative Adversarial Networks (GANs) to generate artificial data that cannot be distinguished from real data by experts (Schaaf et al. 2022), which is elaborated in further detail in Sect. 5.5.1. Furthermore, we apply Transfer and Curriculum Learning approaches to achieve better training results of Artificial Neural Networks (ANNs) (Brillowski et al. 2022b).

Second, we collect additional data. Due to the textile industry's long-lasting history and family businesses, machine parks have emerged over time with heterogeneous and often non-networked machines that cannot contribute to the IoP (Jaspert et al. 2021). Therefore, we are researching retrofitting options to enable companies with older machinery to access the advantages of the IoP (Nakakaze et al. 2022).

Third, the data used to generate the planning tools' recommendations can be captured by monitoring planning processes of experienced process planners (knowledge capturing). One challenge is that planning FRP processes in industry was and still is rather intuitive and based on experience and rarely supported by digital tools (Brillowski et al. 2021b). Thus, neither digital models of previous planning processes nor assessments of possible alternative plans are available that can be used as a data source for the recommendation system (cf. data scarcity dilemma). Therefore, one of our goals was to develop a method to systematically capture implicit process knowledge from domain experts and make that available for later integration as a data source for decision support systems.

A typical approach for this is crowdsourcing (Estellés-Arolas and de Guevara 2012), where micro-tasks (such as image classification for text recognition, autonomous driving, etc.) are distributed to many potential contributors. In this case, data generation through crowdsourcing faces two difficulties: First, there are only a small number of domain experts (Hoffmann 1987), and second, instead of independent micro-tasks, we need to capture sequences of related steps that then represent a process chain in FRP manufacturing (e.g., the use of a tool in process step N depends on the previous step $N-1$).

To compensate for the small number of domain experts, we cannot extract only a few units of knowledge from many, but a few must share their knowledge for longer. We thus developed a serious game-based approach for extracting process knowledge. Serious games harness the motivational potential of games to increase the depth and duration of learning (Breuer and Bente 2010; Brauner and Ziefle 2022). Besides that, the approach can also be mirrored to capture expert knowledge by analyzing the interactions in a game environment. Yet, serious games for

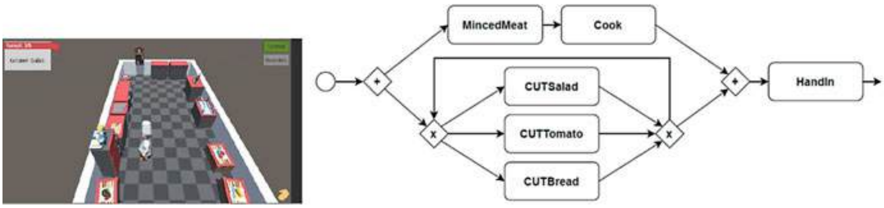


Fig. 5.10 A game-based approach to extract process knowledge from domain experts exemplified through a cooking game. (Images courtesy of the authors from Schemmer et al. 2022). (**a**) Screenshot of the game for extracting process knowledge. (**b**) Extracted process model of a recipe from a user study

capturing process knowledge have not been developed so far. Thus, we developed a proof of concept and investigated whether process knowledge can be captured through this approach, what the quality of the captured data is, and if individual differences influence the quality of the process knowledge extracted through the game-based approach. For the first evaluation, we selected food preparation as a more accessible and familiar scenario. Though it is structurally similar to FRP planning, it does not require the specific domain knowledge and access to participants is easier. Therefore, we developed a web-based serious game recreating a kitchen environment (Fig. 5.10 left), where different ingredients can be processed with different tools and combined to create a dish. All interactions are logged and can be analyzed with process mining tools and metrics.

In an experiment with 60 participants, we could identify process models (Fig. 5.10 right) for all five of the recipes we asked the participants to cook. In this respect, process knowledge could be extracted. However, a drawback was the high variance in the data collected, yielding only satisfactory fitness of the model. Also, our rather laborious approach had little quantifiable advantage over a control condition that queried recipes via an non-gamified drag and drop interface. Yet, clearer task descriptions and less open interactions might yield better results (Schemmer et al. 2022).

In summary, we demonstrated that process knowledge can be extracted with game-based methods, but future work needs to transfer this concept to different and more specific domains and evaluate its applicability. Especially if many different designs for FRP process chains can be captured and then integrated as data sources for providing smarter decision support for FRP process planners.

Other sectors in the textile industry are facing challenges in adopting digital solutions as well. Textile process steps in the Beginning of Life (BOL) and the full Product Life Cycle (PLC) commonly are distributed over poorly orchestrated SMEs with little interoperable data. However, innovation and design in the textile product development require planning and a systems engineering perspective on the process level (Reinsch et al. 2022).

The Digital Capability Center (DCC) is a digital learning factory and acts as a practical demonstrator for digital solutions along the value chain. As a model factory, in the DCC, the reality of textile manufacturing unavoidably is idealized to some degree. Therefore, the data-to-knowledge pipeline in real world requires a powerful component for knowledge acquisition. In the industry, the heterogeneity of process conditions and product variants grow exponentially, digital solutions are hardly standardized, and digital systems often need to be customized for individual use cases (Fromhold-Eisebith et al. 2021). Consequently, the current state of data and model availability in textile production shows open challenges in the IoP. Relevant data and tacit knowledge from interdisciplinary and cross-divisional innovation processes are lacking in order to support model-based and data-driven product development. We investigate the product development of knitted products that require domain knowledge about relations between physical properties, customer requirements, and manufacturing technologies (Beer et al. 2016). In an industrial setting, the development and production of weft and warp knitted fabrics consist of a series of process steps from fiber to end product that includes warping, knitting, and dying. Possible process layouts are diverse and determined by experience-based decisions. Thus, the formalization of domain knowledge and a support system for the full PLC is being envisioned and aimed at Brillowski et al. (2021b).

Semantic web technologies and AI offer potentials for the formalization and the usage of knowledge and data from manufacturing environments. Especially the tasks involved in process analysis as well as data and knowledge acquisition are necessary prerequisites to integrate progress in AI and data science. Therefore, we investigated the current usage of semantic web technologies and especially ontology. We found that many potential application areas of ontology-based solutions remain largely unused in the textile industry. Solutions that allow for integration of interdisciplinary backgrounds, reasoning, and intuitive data access in large and heterogeneous sources of information are rare in the context of textile manufacturing. Most research contributions are directed toward data and service catalogs and the description of textile products either in the design or in the utility phase of the PLC (Reinsch et al. 2022).

We conclude that we need to develop solutions to integrate unused fields of applications of semantic web technologies in the textile manufacturing process. Overcoming this gap and enhancing the accessibility of background information from production is vital for the systematic product development. This applies equally to the integration of AI built on top of tacit domain knowledge and available data from the manufacturing process. However, the textile industry is not only conservative, but also challenges are mentioned repeatedly in the context of textiles and semantics. Unlike established data models and file formats, textile data is barely standardized. Additionally, concepts and entities are very diverse and are regularly only known in the textile domain. Within this diverse field and today's need for interdisciplinary cooperation, information overload is a major problem (Reinsch et al. 2022). We continue our research regarding the development of semantically enriched data models for textile manufacturing and the product development process throughout the PLC.

5.4.3 Analyzing Process Dynamics

Processes in a complex manufacturing environment are rarely in a stable state; instead, they are constantly changing and adapting to new circumstances. Therefore, event data from the same manufacturing line, extracted at two different points in time, can be considered as data from two versions of a process. Process comparison is concerned with the analysis of differences between such process instances. The gained insights can reveal improvement potentials. For example, one subprocess performs better in one process instance than in the other.

Recent approaches in process mining focus on the control-flow perspective (Bolt et al. 2016; Taymouri et al. 2020). However, in manufacturing, the important Key Performance Indicators (KPIs) are time-dependent such as service times. Therefore, comparison approaches that focus on performance are needed. As a first step, based on recent advances in stochastic process mining (Leemans et al. 2021), we developed an approach that detects changes in a process while considering control flow and time simultaneously (Brockhoff et al. 2020). The results can then be used as an entry point for a detailed comparison analysis. One shortcoming of current approach is that it is limited to individual production lines. However, an object-centric view on the production comprehensively considers products, raw materials, orders, etc.

In object-centric view of the process, it is possible to extend the process comparison analysis using an enriched digital shadow of the processes. For example, in described case studies, we have analyzed the process from the car or the printer perspective, although it is possible to analyze the process from other perspectives, e.g., *order*, *customer*, etc. Analyzing the process from multiple perspectives is discussed in a branch of process mining called object-centric process mining (van der Aalst 2019). In Farhang et al. (2021b), we have proposed a standard for Object-Centric Event Logs (OCELs), and several process mining techniques have been developed on top of OCELs (Berti et al. 2022; Cohn and Hull 2009; Fahland et al. 2011). In Farhang et al. (2021a), we proposed a technique to compare the object-centric processes with each other developed a tool on top of that (Farhang and van der Aalst 2022). Using our tool, we have analyzed Heidelberger Druckmaschinen AG data and found the cause of performance problems.

After providing insights and use case studies in process mining and textile industry, we will present the overarching principles serving as a toolbox of omnipresent approaches for data collection and management in the upcoming subsection.

5.5 Overarching Principles

Modern manufacturing and production uses data as a basic resource for improvement. Recent advances have integrated sensor technology, telecommunications, and data-based models to better understand and optimize processes (Brauner et al. 2022; Kagermann 2015). Thus, the concept of data-to-knowledge pipelines has arisen, where data and empirical models serve as a processing engine for generating actionable insights in manufacturing. The IoP tackles challenges emerging from this mix, such as identifying model parameters in complex scenarios, leveraging data-driven models for the generation of insights, or enabling the interoperability of data and ontology. This section first shows techniques for coping with the complexity of industrial data and problems. More specifically, we introduce the usage of generative models to synthesize data leveraging human labels, as well as optimization frameworks for parameter identification. Second, we discuss techniques for understanding of data-driven models, such as concept-based explanations and 3D visualization frameworks. Finally, we detail techniques for increasing the interoperability of data and agents in the industry of the future.

5.5.1 Generative Models for Production

To this day, it is still common to perform quality inspection of manufacturing parts manually through visual inspection. This quality assurance task becomes tedious for the human worker, which results in high error rates and dissatisfaction. Deep learning-based systems that are trained on image data have been increasingly used to automate visual inspection processes, resulting in higher productivity and reduced error rates (Yang et al. 2020).

Using deep learning models for quality control is a popular application of machine learning. Nevertheless, the performance of these models is heavily dependent on the availability of labeled training data. Especially in industrial applications, labeled training data is either associated with high cost or impossible to obtain because of the uncertainty of process measurements. Thus, machine learning methods applicable to data-scarce environments are of interest.

One approach that enables the applicability of deep learning methods is data augmentation. Most commonly, geometric transformations like cropping, flipping, or rotation are applied to artificially increase the amount of training data. In our work, we investigated how well GANs perform as a data augmentation method for synthesizing labeled training data. GANs learn the underlying distribution of the available data and thus are able to generate realistic images from noise. We tested this approach for images of FRP captured during quality control (Schaaf et al. 2022). Our tested generator models were able to synthesize realistic images displayed in Fig. 5.11 and also improve error classification accuracy.

To generate realistic data instances demonstrates that generative models can learn relevant features (i.e., folds and gaps) from data of industrial domains. Although these models do not describe causal relationships, they fit perfectly into the concept of digital shadows. By learning the underlying data distribution from past observations, these models describe a significant aspect of the manufacturing process.

In future work, we investigate the possibility of image synthesis without segmentation maps. Here, we want to train generators of GANs so that the learned features are disentangled from each other. This allows the generation of images

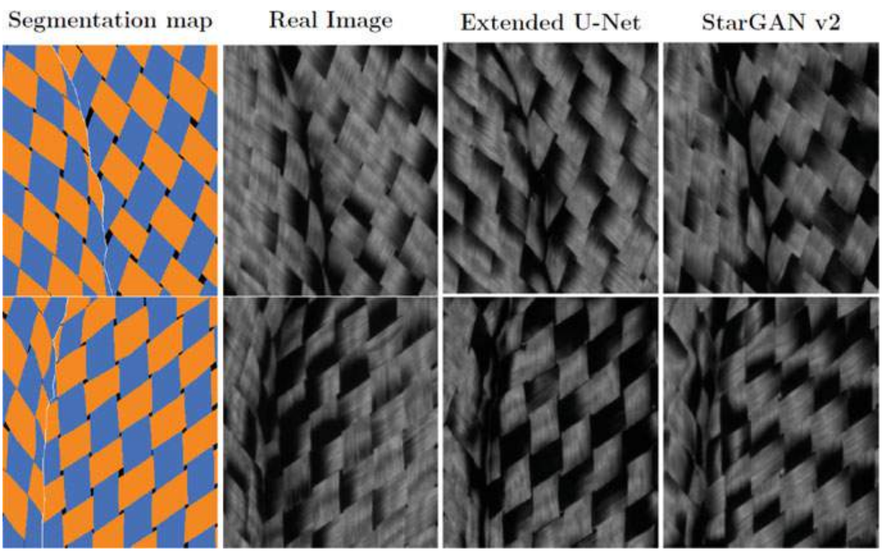


Fig. 5.11 We compared two generator architectures to synthesize realistic images of FRP. Both generators: Extended U-Net (Ronneberger et al. 2015) and the generator from StarGANv2 (Choi et al. 2020) are able to translate the segmentation map to realistic images of fiber-reinforced plastics that preserve material geometry. (Images courtesy of the Institute for Textile Engineering (ITA))

without prior labeling effort. Furthermore, we want to investigate self-supervised learning methods that use training frameworks of GANs for pre-training. The idea is to learn meaningful features unsupervised and fine-tune the model with limited labeled training data afterward. The question of defining and identifying human-understandable features will be presented in the following subsection.

5.5.2 Concept Extraction for Industrial Classification

To apply AI models in critical industrial applications, these must be stable, robust, and trustworthy. However, computer vision-based tasks (e.g., quality control) rely on high-dimensional data and are usually underspecified. This combination makes the used models susceptible to spurious patterns, causing them to be fragile and generating undesired behaviors. In general, this raises the question: Does the AI model do what we want it to do? We tackle this question through the extraction of knowledge from data (or rather from a model trained on these data), and the presentation of this knowledge to a decision-maker. We enable this data-to-knowledge pipeline through the extraction and visualization of abstract patterns (concepts), highlighting them on the input data (here: images) of a model.

As an example, let us consider the quality control of a metal casting process. We can use visual inspection to classify parts into faulty (Fig. 5.13a) or good (Fig. 5.13b), depending on the presence of pinholes or shrinkage defects (Dabhi 2020). This task can be solved using Convolutional Neural Networks (CNNs), but the variety of defects makes a granular (pixel-wise) labeling impractical; thus, it is defined as a classification task between two sets of images. The images contain not only the defects but also other variable factors (e.g., the position of the piece, illumination, or shades in the background), which may pass unnoticed. Ideally, a CNN should distinguish good and bad images, and XAI tells the user how it does it. The XAI should tell the user: I decide good/bad based on the holes. I did not make the decision based on the background.

To extract the knowledge learned by the model, it can be analyzed with global explainability techniques to find which patterns it uses during the prediction process. Then, an expert can validate each pattern (e.g., detection of darker backgrounds, or pinholes) ensuring that they are aligned with the underlying task. For example, users could discard an AI model that makes its predictions based on different background, while they could confirm a model that actually pays attention to the pinholes.

Nonetheless, current explainability methods either are not suited for industrial data or do not reconcile global model explanations with single outcome explanations. On the one hand, feature attribution methods (e.g., Grad-CAM (Selvaraju et al. 2020), IntegratedGradients (Qi et al. 2020)) provide an explanation of which features/pixels are important for a single prediction, but cannot point to which patterns are recurrent, or how one prediction is different from another. On the other hand, global explanation methods, such as concept extraction (e.g., ACE (Ghorbani et al. 2019), VRX (Ge et al. 2021)), perform poorly in industrial use cases. The poor performance is the result of having less data, with less variation, which translates into more rigid and brittle models. Thus, there is a need for global explanation methods which can analyze deep learning models in an industrial context.

By studying state-of-the-art XAI methods for industrial use cases in the IoP, we realized the shortcomings of these methods (scale invariance, lack of traceability, noisy). This motivated the development of a novel concept-based method (Posada-Moreno et al. 2022), which we will present next. Not only is this method able to address the shortcomings of the industrial use case (as we show herein), but it also represents a more general method.

In a general sense, we study the latent spaces of neural networks, finding patterns, and measuring their influence on the model's predictions. The main idea behind our approach is that the structure of the latent space of CNNs reflects what they learn during training. Our approach can be described in four steps, as shown in Fig. 5.12.

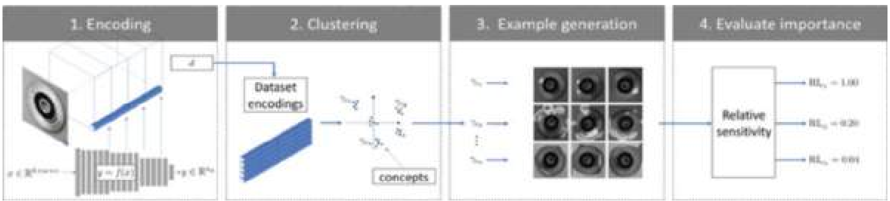
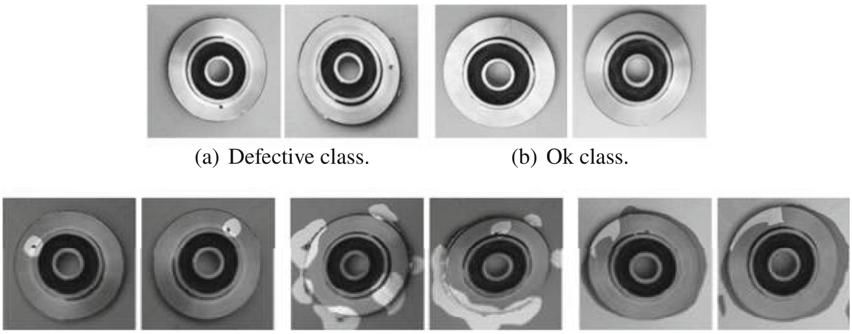


Fig. 5.12 Concept extraction method for CNNs. This method provides a pipeline to extract knowledge from a model, in the form of concepts influencing its prediction process

First, we encode the data set through a representation of the latent space of the CNN. We take the inputs of the model (e.g., images), and encode them in a space, which makes sense in terms of the CNN (activation maps). Second, we cluster the resulting encoded data to mine for patterns. These patterns reflect what has been learned by the network, showing how the CNNs separate the data internally. We call these patterns *concepts*. Third, we extract sets of examples for each concept in the input space of the model. This means we take each mined pattern and find input images which reflect it. These sets of examples provide experts with the means to understand what the pattern is. Fourth, we evaluate the relative importance of each concept based on the sensitivity of the prediction with respect to the pattern.

The core finding of our research is that patterns in the latent space of models are a viable proxy for explaining their global behaviors. Our method outperform state-of-the-art global explainability methods in controlled scenarios and industrial use cases, providing explanations of how a model work, and which types of patterns it has learned to detect (Posada-Moreno et al. 2022). Concept extraction methods can be used to detect undesirable biases learned by a model, explain what features are being detected, and how complete or aligned the prediction process of a model is.

As an example, we present the case mentioned above, where a CNN is trained to perform the quality control of casting pieces. After training a CNN to classify upcoming images as defective or ok, the latent space of the model was analyzed, applying our concept extraction method (Posada-Moreno et al. 2022). The main extracted concepts are shown in Fig. 5.13c, d, or e. The first concept corresponds to pinholes, which is the most important cue for the prediction of defective parts. The second concept corresponds to malformed edges of the part. This concept



(a) Defective class. (b) Ok class.

(c) concept 1, RI=1.0. (d) concept 2, RI=0.2. (e) concept 3, RI=0.04.

Fig. 5.13 Data set of casting parts, where the task is to classify defective (**a**) and ok parts (**b**). After training a DenseNet-121 to perform the said task, our method can analyze what was learned by the model. Figures (**c**), (**d**), and (**e**) show the main extracted concepts, which can be used by experts to ensure compliance with their prior knowledge. The most important concept used by the model are pinholes (**c**) (with relative importance of 1.0), followed by malformed edges (**d**) (RI of 0.2), which the model learned to detect. Concept 3 shows a bias in the background (RI of 0.04), which was detected after a first stage of training, and allowed experts to realize and mitigate this phenomenon by acquiring new sample data also contributes positively to the prediction of defective classes. Similarly, the third concept shows background, with an importance close to zero. These concepts were learned by the model without being explicitly annotated and can be used by experts to ensure that the model decision-making process is aligned with their understanding of the problem.

Our concept extraction method (Posada-Moreno et al. 2022) has been proven as an effective tool for analyzing CNNs, allowing the validation of expert knowledge and the identification of spurious patterns (undesired behaviors). This success has opened several relevant questions for future research. First, we will investigate the application of concept extraction to other use cases in the IoP. Second, we will explore the transferability of our method to other data modalities, such as time series. Finally, the question of how to measure the correctness of a concept extraction method remains.

5.5.3 Inverse Problems via Filtering Methods

Many modern AI methods, such as training of neural networks or clustering, are mathematically high-dimensional and may lead to nonlinear optimization and parameter identification problems, which might be ill posed (Engl et al. 1996). Therefore, in-depth understanding of the underlying methods is relevant to judge the quality and the results of modern AI techniques. Further, many black-box methods may fail at standard tasks, and a deeper understanding of the properties is required to provide suitable solutions and alternatives. Finally, many actual problems, like multi-objective tasks, cannot yet be treated with current AI techniques due to their limited scope. Moreover, most industrial problems are subject to uncertainty, since data and measurements may be affected by noise, the physics of processes could be not completely known, and/or small variations in the production process may occur. This has so far not been treated in classical AI algorithms.

The state-of-the-art methods are not suitable for current applications due to, for example, a lack of possibility to include multi-objective optimization, the requirements of analytical gradients of models that are usually expensive or not available (e.g., in case of models described by neural networks), and the missing knowledge on how to update algorithmic parameters (e.g., hyperparameters for neural networks or weights for multi-objective procedures). Moreover, there is a lack of methodologies to include and quantify the uncertainty existing in the processes.

Our contribution on the IoP vision focuses on the development and the analysis of numerical methods for complex optimization and parameter identification tasks. In this framework, we focus on a numerical method for solving nonlinear optimization and parameter identification problems, namely, the ensemble Kalman filter (EnKF). Furthermore, we provide an efficient numerical method to analyze the propagation of the uncertainty. The EnKF is an iterative filtering method designed for gradient-free optimization, hyperparameter search, and multi-objective optimization (Herty et al. 2021; Yegenoglu et al. 2020). It is a general algorithm with convergence guarantees and stabilization properties which have been proven in Herty and Visconti (2019, 2020). Besides the natural idea of implementing directly the iterative particles scheme, we developed an abstract algorithm with parameter adaptation exploiting the mathematical properties and insights of the EnKF procedure. Both the approaches have been implemented and tested (Herty and Iacomini 2022a). Our algorithm has been applied in the field of automatic control (Schwenzer et al. 2020). Other applications in laser technology and plastic processing are being explored.

Moreover, we investigated the propagation of input uncertainty through a process, e.g., how the uncertainty in the initial data propagates through a model. We provide a method for the expansion of noise in a series. Then, we analyze the equations for the coefficients of the series and develop an efficient numerical treatment of those (Gerster et al. 2021). This allows us to perform a risk estimation, e.g., to detect high probability areas of instabilities, failures, and rare events (Herty and Iacomini 2022b). Although the algorithm and the theoretical framework have to be adapted to the specific process, the methodology is already available, analyzed, and implemented.

Here we provide an example of a developed method for parameter identification. The problem of finding the unknown parameters u in a non-differentiable model $\mathcal{G}$ and given data y is formulated mathematically as:

$$u^* = \mathrm{argmin}_{u\in X}\Phi(u, y), \quad \Phi(u, y) = \frac{1}{2}\,\|y - \mathcal{G}(u)\|^2 \tag{5.1}$$

For the design of an efficient method, we move to an equivalent description on a mesoscopic level by means of partial differential equation (PDE), which allows us to describe the evolution of the probability distribution of the parameters $f = f(u, t)$, at iteration t. The equation reads as follows:

$$\partial_t f(u, t) - \nabla_u \cdot (\mathcal{C}(f)\nabla_u \Phi(u, y) f(u, t)) = 0, \;\; f(u, 0) = f_0(u) \tag{5.2}$$

for some nonlocal operator $\mathcal{C}(f)$, see Herty and Visconti (2019).

Equation (5.2) can be efficiently discretized by a particles method with $j = 1, \ldots, J$ particles sampled from the initial distribution f_0. This leads to an iterative scheme for candidates such that $\frac{1}{J}\sum_{j=1}^{J} u_j(t) \approx u^*$. The full procedure consists of the following update for $u_j^n = u_j(t^n)$:

$$u_j^{n+1} = u_j^n + C(u^n)\mathcal{G}^T\Gamma^{-1}\left[y_j - \mathcal{G}(u_j^n)\right]$$

$$C(u^n) = \frac{1}{J}\sum_{j=1}^{J}(u_j^n - \overline{u}^n) \otimes (\mathcal{G}(u_j^n) - \overline{\mathcal{G}})$$

$$\overline{u}^n = \frac{1}{J}\sum_{j=1}^{J} u_j^n \quad \overline{\mathcal{G}} = \frac{1}{J}\sum_{j=1}^{J} \mathcal{G}(u_j^n)$$

and the solution u^* is given by the mean of the particles at the end of the evolution at $n = \infty$. This method has been extended in the IoP to a stabilized version, (Armbruster et al. 2022) and a multi-objective framework (Herty and Iacomini 2022a).

We have extended classical AI methods by adaptive algorithms taking into account the particularities of the engineering applications, like nondifferential models (Herty et al. 2022), multi-objective tasks (Herty and Iacomini 2022a), and unknown hyperparameters. Novel methods have been developed and numerically analyzed. Furthermore, they have been implemented and tested. The templates for algorithms have been designed and are available. Those can now be implemented and adapted to the specific programming environment and computer architecture.

We have tested and validated sample problems from different domains and disciplines, e.g., Schwenzer et al. (2020).

Moreover, a methodology for investigating the propagation of uncertainty and performing a risk estimation has been proposed and efficiently implemented.

Future work will focus on developing prototypes of algorithms which might need improvements in computational efficiency, also for dealing with very high-dimensional parameter space, which is still challenging. Moreover, we plan to blend the new methods with existing AI methods to provide a larger toolbox to analyze and solve issues coming from engineering applications.

5.5.4 Immersive Visualization of Artificial Neural Networks

ANNs are the most popular class of machine learning models to date due to their superior performance compared to previous approaches. In many cases, their superiority can be attributed to their complexity, as ANNs can have millions-billions of parameters. While this allows the model to encode a lot of information about the given problem, such as the digital shadow of a production process, this encoding remains opaque to the user. It is currently not possible to fully understand the reasons for the decisions made by ANN, nor is it possible to extract knowledge about higher concepts they might have learned. Nevertheless, without this ability, there is a trust gap between humans and ANN that limits their usefulness in production systems. This is commonly referred to as the black-box problem (Castelvecchi 2016).

To combat this problem, the field of XAI has recently gained traction. It describes a collection of tools that enhance our understanding of AI techniques by means of explanations. One way of generating explanations is through visualizations. When showing abstract data in a visual manner, users can use their own intuition and ability to recognize patterns to gain intuition or find hypotheses. This facilitates an exploratory process that can be further enhanced by interactivity to quickly explore the space of visualization parameters. We want to apply this concept to the entire ANNs.

While visualizations like TensorBoard (the built-in visualization of TensorFlow (Abadi et al. 2016)) exist, which give an overview of the structure of ANN, they do not visualize the learned parameters. Yet, they make use of node-link diagrams, which is a common concept when visualizing ANNs. Likewise, node-link diagrams are often used to explain the basics of ANNs. They show how individual neurons are connected and highlight their similarity to biological neural networks. This brings up the question if this concept can be extended to visualize full-scale ANNs to give insights into their inner working.

The main challenge with this idea is the large size of parameters that would need to be visualized for even relatively small ANNs. Showing them in a 2D visualization becomes infeasible. For this reason, 3D visualization of ANNs has become an active area of research. As an example, Harley (2015) shows a working ANN as a 3D node-link diagram. They show individual values computed by the ANN as boxes and the network's weights as edges between them. For convolutional units, the boxes are arranged in a grid, so that they resemble the filtered image. To avoid clutter, they only show edges that connect to one node, which is selected by the user.

Following this trend, we applied a 3D node-link visualization, similar to Harley (2015), to a real use case in the area of production research (Bellgardt et al. 2020). We visualized a neural network controlling a robotic arm, showing the activation values live during operation. Our expert review revealed that the visualization is useful to understand the scale of the network and find potential problems, such as an incorrect implementation of filter kernels. Nevertheless, the experts commonly requested to see more of the edges at the same time. The visualization of fully connected units, which were simply arranged in a line, was not perceived to be helpful.

From the positive results of the prototypical implementation described above, we conclude that the area of 3D node-link visualization of ANN should be investigated further. It is of particular interest whether different layouts of nodes in the fully connected layers can make them more useful and how the visualization of edges can be improved. Additionally, we conceive further research questions, such as whether visualizing other aspects of the network, than just activation values and weights, is feasible. Unfortunately, pursuing these questions based on our initial prototype would have been difficult, since it was constructed rigidly for its specific use case.

Instead of developing another specialized application from scratch, there seems to be a need for a universal framework that allows rapid prototyping of 3D node-link visualizations for ANN. Such a general framework would need to be integrated into the tools that experts working on ANN are using and allows designing visualizations in a high-level programming language. Since most ANNs are developed using Python frameworks, it is a reasonable choice for the visualization framework to be available as a Python framework as well. This way, the ANN experts could prototype their own visualizations, ideally without the need to be familiar with programming in 3D environments and computer graphics.

Developing the whole framework in Python would not be feasible, as the intense performance requirements of 3D rendering are not met by a high-level language like Python. Hence, the rendering part of the application should be split off and handled by a more optimized rendering engine. This makes it tempting to integrate the Python environment within the engine, since modern game engines

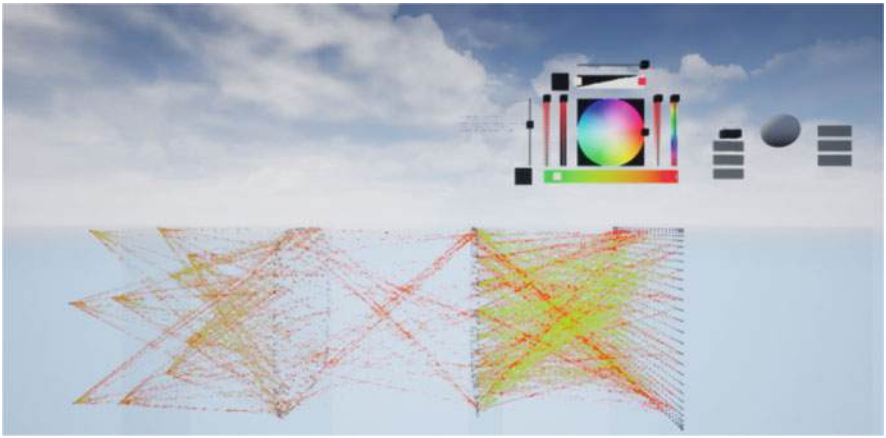


Fig. 5.14 The ANNtoNIA framework enables rapid prototyping of immersive visualization for ANN to facilitate visualization research and improve explainability

often have Python support. This is the solution that was chosen in Aamir et al. (2022). Nevertheless, we argue against this method, since integrating the ANN code this way will still require knowledge of the game engine. Additionally, this would limit the ANN and the visualization to run on the same machine. Since both training/inferring ANN and 3D rendering are performance-intensive tasks, it might be desirable to split them to different machines. For this reason, we argue that it is best to couple the Python part and the rendering part using a network interface.

We develop this visualization framework under the name ANN to Node-link Immersive Analytics (ANNtoNIA) (Fig. 5.14 shows a screenshot) and plan its release under an open-source license.

5.5.5 IoP-Wide Process Data Capture and Management

In agile manufacturing, the seamless integration of processes, data, and information systems throughout the supply chain, even across organizational boundaries, is crucial. Today, data is frequently locked in local data silos and insufficiently linked to products, manufacturing processes, and its own lineage. The lack of standardized and interoperable data management solutions hinders the exchange of data across the IoP, and therefore, meaningful, industrial collaboration.

The FactDAG interoperability model (Gleim et al. 2020a) addresses this issue, by adapting and extending the FAIR data principles (Wilkinson et al. 2016) for industrial data, ensuring data to be findable, accessible, interoperable, and reusable. From a technical perspective, FAIRness requires persistent identification of data, open-access protocols, and rich metadata. The FactDAG itself integrates these three aspects in a directed, acyclic graph (DAG), consisting of immutable data elements called Facts which are linked using standardized provenance relations (Gleim et al.

2020b) based on information from the creating processes, involved systems, and responsible agents. Each Fact has a globally unique, persistent identifier, called FactID. The FactID identifies the responsible authority (e.g., the company owning the data), a data resource, and a specific revision of that resource and allows data to be immutably referenced across the Web (Gleim and Decker 2020). The combined provenance metadata is crucial for the reusability of data and needs to be reliably captured, ideally supported by automated software components.

With the FactStack (Gleim et al. 2021a), an open-source implementation of the FactDAG model, we support an end-to-end data management process based on established open technologies, Web standards, and linked data principles (Bizer et al. 2009). FactStack supports the data management life cycle, ranging from data capture over data preservation to data sharing and finally data reuse. Each data resource is automatically versioned and the persistent identification of data elements enables reliable references to specific revisions of data elements, even across system and organizational boundaries. As such, data and processes can be linked with process provenance throughout the global supply chain in a simple and efficient manner. The automatic collection of provenance and metadata supports data quality and enables interorganizational interoperability and data reuse. Utilizing the FactStack and its underlying linked data principles and technologies, data can be discovered and accessed through the Internet across organizational boundaries using standardized access protocols, such as HTTP and compatible extensions (Gleim et al. 2021b). Nevertheless, data and metadata may still be managed using end-user-friendly graphical user interfaces, e.g., directly in the traditional computer file system (Müller and Gleim 2021).

Capturing and managing process data across agile supply chain enables data- and AI-driven process optimization, e.g., the generation of process models and planning of industrial processes across organizational boundaries by autonomous agents.

5.6 Conclusion

The digital transformation of production enables faster, smarter, and more efficient production and improves value creation (Bruner 2013; Boyes et al. 2018; Brauner et al. 2022). In this chapter, we illustrated how to realize the IoP's vision of integrating data from human experts, machines, and processes across the design, manufacturing, and use cycle to transform data into actionable insights. We introduce the idea of autonomous agents that can query the DSs provided by different users, across different processes, and beyond company and country borders. The applicability of this approach was demonstrated in the two examples of generating pass schedules in hot rolling and injection molding. We surveyed some of the challenges facing the digital transformation on the different abstraction layers of an industrial environment. A central element is bridging the gap between people and machines on the one hand and algorithms and data on the other hand. We introduced "data-to-knowledge pipelines" as a core concept and illustrated the realization of validated self-adaptive production systems.

The work for realizing these pipelines covered various directions. First, we showed that ontology in textile engineering can capture expert knowledge and that it can be integrated in the data lake and the WWL. We further addressed the point of data scarcity in production where data collection can be expensive, time-consuming, and error-prone. This is done by employing GANs to synthesize realistic additional training data for ML applications. By augmenting the training data set with the generated images, the accuracy of a defect classifier for FRP improved significantly.

The industrial usage of ML and especially ANN increases significantly. Nevertheless, the prevalent black-box models are often insufficiently trusted. Hence, we introduced approaches to increase the explainability of the resulting ML models (XAI). On the one hand, by proposing methods to identify high-level explanations (concepts) learned by ANNs and by creating a framework for immersive visualizations that disclose an ANN's structure and functionality. On the other hand, we improved methods for complex optimization and parameter identification to improve the quality of production data. These methods facilitate the validation of models, ensuring that expert knowledge is aligned with their decision-making process.

Further, to improve the explainability, we used gray-box models for robot control and demonstrated this in machining. We proposed a structured neural network for learning the dynamics of an industrial robot. It integrates forces that are difficult to model, such as friction, as ANN and incorporate these into physical models. This combines the advantages of both analytical and data-driven modeling.

For improving robot movement in laser manufacturing, we use RL to generate laser-specific policies for steadier robot trajectories. To realize self-adaptive systems, we further improve these policies by feeding back in situ measurements.

We provided examples of data-to-knowledge pipelines that improve the performance of LPBF-based additive manufacturing processes by detecting defects and adapting the process.

Our data-to-knowledge pipelines have interfaces in the form of smart DSSs that assist operators and managers in making informed production decisions. We integrated AI in DSSs in textile engineering and investigated design requirements for ensuring usability, trust, and acceptance. To demonstrate this, we realized a process planning assistant that builds on historical planning data and experts' knowledge to provide sound and complete process plans based on given optimization criteria.

For enabling safe HRI on the shop floor, we employed BT because they offer higher reactivity, flexibility, and modularity compared to other robot programming approaches. We extended the node types with human-action nodes that allow the robot to anticipate and react to human tasks. To further increase the safety of and confidence in reconfigurable CPPSs, we introduced runtime monitoring to bridge the gap between testing and formal verification.

We model production processes to facilitate process identification, analysis, optimization, comparison, prediction, and conformity checking. In addition, we introduced the OCELs standard and used it for approaches of process visualization and data analysis through object-centric process cubes.

Although the work presented here shows promising steps toward the digital transformation of production, many further milestones need to be passed to achieve the vision of the IoP. First and foremost, the holistic integration of the currently often unconnected applications demonstrated here must be further advanced. Further, the methods and concepts developed must be transferred to the multilayered and very different applications in production, and their suitability must be then verified across the various production domains. Second, the existing methods must be further refined and improved, for example, by using the human digital shadow (Mertens et al. 2021) to provide individually tailored support systems that are context-, task-, and – above all - human-aware. Finally, the data must be integrated into a global WWL that will interconnect research labs and production sites across company and national boundaries (Brauner et al. 2022; Gleim et al. 2020a).

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Part III

Materials

Materials Within a Digitalized Production Environment

6

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Abstract

Materials serve as the foundation of the technical framework on which modern society relies every day. Generations have developed new materials, tried to understand the origins of their properties, and found ways to predict them. Modern computational tools have vastly expanded our capabilities to make predictions, not only of material properties but also of component properties and of the component health status over its life cycle. Integrated Computational Materials Engineering (ICME) aims at simulating the material and component properties along the complete process chain and across the length scales from microstructure to component scale. In this way a digital twin of the material or component can be generated, which can be leveraged to facilitate gains in productivity and service life of technical systems. By reducing the complexity of models for the digital twin where necessary, combining them with in-process data using innovative sensor technology and suitable mathematically driven approximation procedures such as machine learning, it is possible to conceive a digital material shadow that resolves elements of the dilemma between data granularity, data volume, and processing speed to enable process monitoring and control for materials processing. To enable communication between humans and machines it is necessary to create a strictly defined language in the form of ontologies. Ontologies are typically domain-specific, but care must be taken to make them consistent across domains. Integrated Structural Health Engineering (ISHE) aims at predicting and monitoring the health state of components over their entire life cycle, enabling timely replacement of components and avoiding costly and possibly life-threatening failures. In particular when components are subjected to cyclic loading, their structural health does not primarily depend on the average material properties, but on the presence of more or less statistically distributed defects. These defects are intrinsic to materials processing, cannot be completely avoided, and evolve during various stages of the production process. The objective of ISHE is to predict their formation and evolution during the production process and their impact on the component structural health during its life cycle. It is clear that the material and component properties are strongly dependent on the process by which they are produced. Therefore, many of the topics discussed in this part have relational counterparts in Part IV, “Production”.

6.1 Introduction

The development of computer power and simulation methods has led to enormous advances in the last few decades. Simulation models are increasingly used for material and process development and a large number of simulation tools are now available. Today, they describe phenomena on all time and length scales relevant to materials and can often be run on a standard laptop, even for complex simulations. Currently, these software solutions have reached a level in their respective fields that allows valuable contributions to modern design tasks in knowledge-based production models. The aim is to provide digital material and component models (digital twins and digital shadows) that can be used in the wider context of the Internet of Production. Three Workstreams have been defined to highlight various aspects of the ICME and ISHE methods and show how digital twins and digital shadows can be derived and leveraged to enable a targeted response to the individual defect density. The Workstreams to be described in the three following ► Chaps. 7, "Material Solutions to Increase the Information Density in Mold-Based Production Systems", ► 8, "Toward Holistic Digital Material Description During Press-Hardening," and ► 9, "Materials in the Drive Chain – Modeling Materials for the Internet of Production."

6.2 ICME in a Production Environment

Overall, the complex interaction of atomistic processes, thermodynamics, process conditions, microstructure development, material, and component properties can only be described by combining different simulation and machine learning (ML) tools within the framework of an "*Integrated Computational Materials Engineering*" *(ICME)* approach.

The *history of ICME* actually began with the first use of computers in materials science at all and has led via "Computational Thermodynamics" to the CALPHAD methodology (Lukas et al. 2007; Saunders and Miodownik 1998) and further to spatially resolved simulations of microstructure formation using the multi-phase field methodology, to crystal plasticity models and many more. Currently, a heterogeneous variety of hundreds of software tools related to ICME is available (Schmitz and Prahl 2016).

The *basic idea of ICME* is to simulate the material and the component through the complete process chain, from raw materials to finished component, and across the length scales, from atomic scale to component scale. The simulation results from one step in the process chain then form the input for the next step. In this way digital material/component twins and shadows can be constructed. The fast digital shadows with specifically reduced information content can be augmented by in-process data and can, thus, be used to control the process to achieve the final desired component properties. The properties of materials are largely determined by the microstructure, i.e., the distribution of phases, grain size (crystallite size), amount and distribution of dislocations, etc. The formation of the microstructure is ultimately determined by processes on the atomic scale. To reach component scale properties it is therefore necessary to use model-reduction and scale bridging to sufficiently coarse-grain the models to make them usable at the component scale without sacrificing the physics inherent in the lower scale models (Heo et al. 2021).

ICME in contemporary material concepts aims at improved properties by adapting and tailoring the microstructure. Several trends are of interest here: the quantitative evaluation of very small microstructure components on the nm scale, the description of very inhomogeneous microstructures, a higher level of alloying and the interaction of different alloying elements associated with it, the incorporation of metastable phases, and eventually the determination of effective material properties by means of mathematical homogenization and virtual tests *The use of ICME methods* leads to an understanding of the underlying physical phenomena, enables faster material and process development, and increases process reliability and robustness.

Applying *ICME for new material classes and new production methods* allows efficiently rethinking design approaches and entire components. An example is performance-oriented material development under the aspects of strain hardening engineering (SHE) using the possibilities resulting from the use of additive manufacturing processes (AM).

6.3 Integrated Structural Health Engineering

The fatigue strength of a component is often determined by defects. These defects can either be surface defects created during the production or usage as a result of, e.g., wear or corrosion, or they can be internal defects, typically created at the very beginning of the process chain and modified throughout the process chain. Critical internal defects may be relatively rare, but even if only one component in one thousand has a critical internal defect, which actually reduces the component lifetime, the failure of this component must be prevented by timely repair or replacement. Traditionally, this is achieved by regular maintenance intervals where components are inspected for damage. Within *Structural Health Monitoring* (SHM) (Farrar et al. 2001; Strantza et al. 2015) this can be augmented by using sensors to capture damage in situ using, e.g., changes in acoustic, vibrational, or compliance properties. This is particularly important when the component is not easily available for inspection. *Integrated Structural Health Engineering* (ISHE) offers a more holistic approach by including also the production process chain and extend the ICME generated Digital Material Shadow to a Digital Component Shadow, which includes the components health status with a prediction of its residual lifetime. Defects can be assumed to be distributed statistically within the material, but only the tail-end of the distribution is of particular interest here. By the combination of sensors and machine learning methods, process conditions that can result in defect formation can be identified. The evolution of the defects can be predicted and influenced with the help of the ICME tools used to produce the Digital Material Shadow. Statistical methods combined with ML methods are then used to predict their location within components and the resulting impact on the component's predicted fatigue life.

6.4 Machine Learning

Machine learning methods can complement or replace simulation models if sufficient data are available. Due to the black-box behavior of most of these methods, increasing the understanding of their outcome is of great importance to improve their prediction quality. For this purpose, mathematical tools can be applied. To give an example, a special type of residual neural networks (ResNets) has an underlying structure which allows for analyzing at least simple ResNets using mathematical techniques from kinetic gas dynamics (Herty et al. 2022). Furthermore, classical or deep neural networks can be linked to physics by incorporating the governing equations of the problem at hand. The resulting physics-informed neural networks (PINNs) compute the residuals of the underlying partial differential equations applying automatic differentiation of the neural network outputs to optimize the training of the network (Raissi et al. 2019). If the governing equations are only partly known, PINNs even allow for the data-driven discovery of underlying physics, e.g., by determining unknown parameters.

A common problem of an already trained machine learning method is its limited reusability. A neural network may have to be retrained if, e.g., a material component in a production process is modified. Efficient transfer learning algorithms such as ensemble Kalman filtering (Kovachki and Stuart 2019) allow for a fast retraining in settings where only few external conditions change (Herty et al. 2021).

6.5 Ontologies for ICME

Future ICME will be based on interoperability. The interaction – i.e., "interoperability" – between different simulation tools, between experiment and simulation, between product and manufacturing process, between human and computer, between models and data, and between different knowledge and experience domains requires a "common language" which is understood by both machines and humans. Especially enhanced interoperability between data and models will lead to new models being based on production data or on experimental data (AI) and especially to model- (or physics-) informed neural networks, e.g., Torabi Rad et al. (2020).

Current trends in ICME thus are based on the development, the use, and the *modular configuration of ontologies*. Ontologies are at the top of the semantic spectrum stretching from symbol, via keyword, thesaurus, syntax, semantics, taxonomy, ontology eventually up to epistemology (Obrst 2010). In addition to the hierarchical "isA" relation" used in taxonomy, ontologies provide further relations between different classes of things. These additional relations may be arbitrarily selected ("lightweight ontologies") or are based on fundamental concepts of analytical philosophy like mereology (Casati and Varzi 1999; Schmitz 2020), mereotopology (Schmitz 2022), causality (Ghedini et al. 2022), and semiosis (Atkin 2010) being formulated in first-order logics ("heavyweight ontologies").

Application of ontologies in industrial settings requires the fundamental philosophical concepts to be exposed to harsh environments of industrial production. Such applications in fact can be attained when harnessing a foundational core ontology by suitable domain ontologies. The *Elementary Multiperspective Material Ontology* EMMO (EMMO 2022) is a foundational ontology providing the framework for standardized integration and a modular, re-useable configuration of a variety of domain ontologies. EMMO in this context is not the only foundational ontology. Other foundational ontologies are BFO (Arp et al. 2015), BORO method (BORO 2021), Dublin Core (2022), GFO (Herre et al. 2007), Cyc/OpenCyc/ResearchCyc (Cyc 2022), SUMO (2021), UMBEL (2021), UFO (Nardi et al. 2013), DOLCE (Borgo and Masolo 2010; Gangemi et al. 2002), WordNet (2022), and OMT/OPM (Dori 2002; OPM 2022). Their harmonization toward a unifying Top Reference Ontology (TRO) is an on-going effort of a European research project (OntoCommons 2022).

6.5.1 Ontologies in Materials

The 118 chemical elements in the periodic table being relevant in everyday life are a result of combinations of only a subset of the elementary particles. The standard reference covering chemical elements is the IUPAC Gold Book (Gold 2019). Combinations of different chemical elements lead to an exploding variety of possible substances and arrangements like molecules, crystals, nanoparticles, and eventually all bulk materials constituting the macroscopic production world. For almost each of these classes there exist some individual taxonomies or ontologies like the CheBi ("Chemical Substances of Biological interest" (ChEBI 2018)), the Nanoparticle Ontology (NPO (Thomas et al. 2011)), Environmental Material Ontology (ENVO (Buttigieg et al. 2016)), or the Crystallographic Information File (CIF (Brown and McMahon 2002)). Further classification of materials often proceeds by chemical composition. Ceramics in general are distinguished into oxides, carbides, nitrides, silicides to name a few. Metals and alloys are first classified by the major chemical element like Al-alloys, Fe–alloys/steels, Ni-alloys, Cu-alloys. Taxonomies of technical materials are widely used in characterization and reliability fields of materials engineering to distinguish various industrially used alloys, metals, and ceramics. The International Alloy Designation System, for example, is the most widely accepted classification and naming scheme for aluminum-based alloys enabling automated and human interpretation of the type of materials by a digit-based encoding system, e.g., "Al 6061" (Aluminium Alloy 2022). Even for the same overall chemical composition, however, the properties of the resulting material still depend on the way it was further processed, e.g., in tempering processes. The respective temper designation thus follows the digit-based designation number with a dash, e.g., 6061-T6. The definitions for the tempers are, e.g., (for a full list see (Aluminium Alloy 2022)): -F (as fabricated), -H, and -T. Current Material Databases (e.g. (Ansys Granta 2022)) provide compilations of processing and property data for a huge variety of alloys, compounds, and substances.

From the end user perspective, the ultimate functionality of the material is the major topic of interest. These end users are not at all interested in any detail of the material like its microstructure or its composition. These users are interested in knowing the effective properties of the volume filled by the material. Current trends of materials taxonomy and more specifically ontology developments thus direct toward a sub-domain and/or particular application specific focus, e.g., Ceramics (van der Vet et al. 1994), Structural Materials (Ashino 2010), Composites (Premkumar et al. 2014), Alloys (Zhang et al. 2016), Catalysts (Takahashi et al. 2018), or Functionally Graded Materials (Furini et al. 2016). In many cases nowadays the microstructure of a material is considered as the state variable defining the materials properties. Semantic microstructure descriptions thus increasingly become subject of ontology development using a standardized nomenclature (CWA 17284 2018), suitable metadata descriptions (Schmitz et al. 2016), and eventually a foundational ontology framework like EMMO. EMMO compliant domain material ontologies have already been developed for characterization (Morgado et al. 2020) and crystallography (CIF ontology 2022), and currently are under development for microstructure and thermodynamics within task groups of the European Materials Modelling Council (EMMC ASBL (EMMC 2022; EMMC Task Group 2022)).

6.5.2 Ontologies in Production

Quite a number of ontologies related to different aspects of production have emerged over the years, Fig. 6.1.

They are not harmonized neither in terms of their underlying foundational ontology nor in the general use ontological relations being somehow arbitrary and not being based on first-order logic concepts. Accordingly, most of them have to be considered as "lightweight" ontologies. The diversity of the underlying foundational ontologies and the heterogeneity of the ontological relations being used make this variety of ontologies hardly be configurable and mutually interoperable. An example is the ADACOR ontology (Borgo and Leitão 2007) being based on the DOLCE (Borgo and Masolo 2010; Gangemi et al. 2002) foundational ontology.

Ontology name	Scope	Typical Application
PRONTO	Product	Material requirements planning
ONTO-PDM	Product, Process, Resources	Simulation of distributed activies for manufacturing simple product prototypes
PSL	Process, Resources	Discrete-event simulation
MSDL	Process, Resources	Automation of various tasks throughout virtual enterprise life cycle
MASON	Product, Process, Resources	Multi-agent systems for manufacturing
MSE	Product, Process, Resources	Resource e-planning
MRO	Product, Process, Resources	Development of application-specific ontologies
ADACOR	Product, Process, Resources	Development of manufacturing control applications
MCCO	Product, Process, Resources	Explore interoperability across product lifecycle domains

Fig. 6.1 Table of some contemporary ontologies in the area of production. (Reproduced from (Borgo and Leitão 2007))

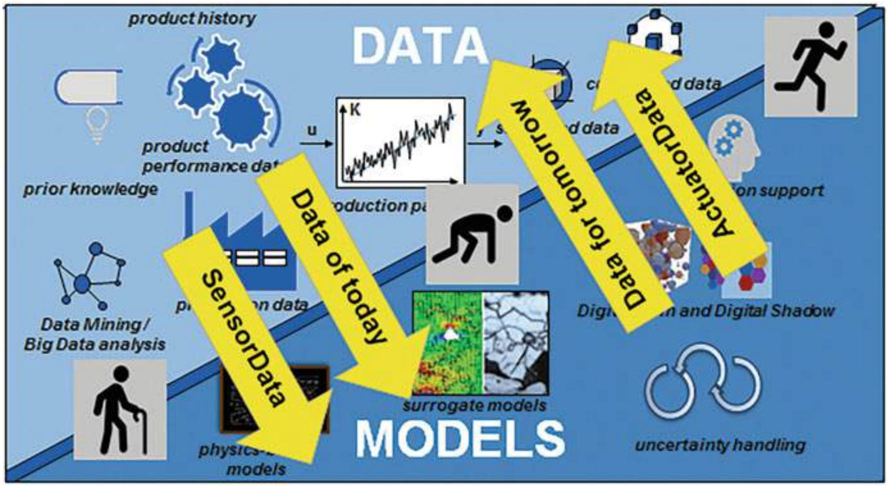

Fig. 6.2 *Sensor DataStreams* and *ActuatorDataStreams* are the only interfaces providing knowledge of the production system or allowing to influence its behavior. Solely based on these data, a neural network could be trained or other models be informed. No notion about the actual production machinery would be necessary

Scope of all types of production ontologies is to make production – and also all product – data FAIR meaning Findable, Accessible, Interoperable, and Re-usable. Production data as well as in-service life product data can be classified into dynamic *DataStreams* and static *DataTraces. DataStreams* can further be sub-classified into *SensorDataStreams* and *ActuatorDataStreams. SensorDataStreams* provide all information about the actual state of the production system. Their recording into static *DataTraces* allows tracing the history of the entire production system. *DataTraces,* i.e., stored information, also comprise all static information about the production system like information on machinery, their arrangement in the production system, geometries of product components, etc. The *SensorDataStream* along with the available *DataTraces* comprehensively describes the actual status of the production system including short-term evolution trends and thus the "data of today." The *ActuatorDataStream*, in contrast, comprises all types of data allowing to intentionally and actively "change" the state of the production system, e.g., by changing controller settings or simply stopping a machine. The *ActuatorDataStream* thus provides the data for an intended behavior of the production system "tomorrow," Fig. 6.2.

6.5.3 Modular Configurable and Re-Usable Ontologies

Contemporary ontologies in many cases have been developed independently and aiming at adequately covering the knowledge of the respective domain. In many

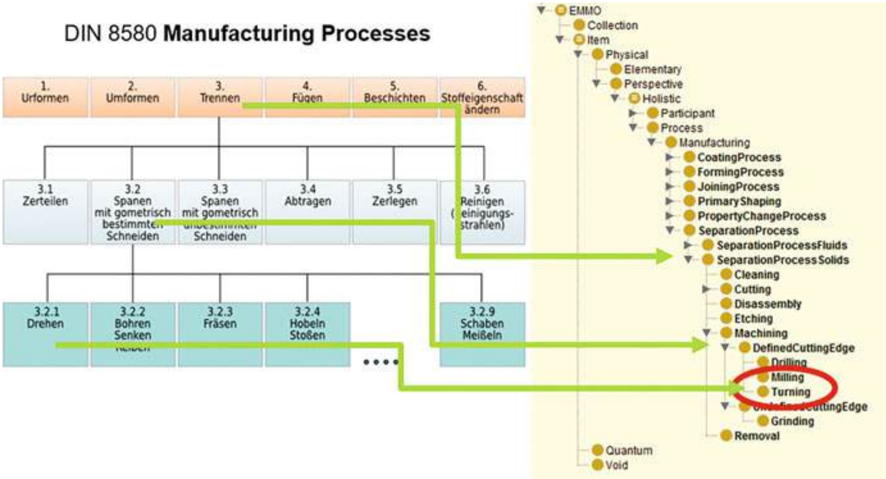

Fig. 6.3 ManufacturingProcess ontology based on DIN 8580 and its integration into the EMMO framework. Not all subclasses of all manufacturing processes are shown

cases the full specification of notions also being important for other domains was necessary. Examples for ontologies of common interest and likely to be used in many domain ontologies are, e.g., ontologies for SI-units, for basic mathematical operations and expression, for basic chemistry, thermodynamics, and crystallography to name a few. A modular configurable set of mid-level ontologies bridging between the foundational ontology and the application-oriented domain ontologies thus is highly desirable. The *Elementary Multiperspective Material Ontology* EMMO supports such a strategy and quite a number of mid-level and domain ontologies are already publicly available (EMMO Middle 2021).

One of the scopes of IOP work was to structure the domain of "Industry 4.0" and to identify the required domain ontologies, which have to match the language of industrial production. In detail EMMO compliant domain ontologies/taxonomies for *ManufacturingProcesses*, for *ProductionSystems*, for *ContinuumMaterials*, and for *ModellingSoftware* were developed. The *ManufacturingProcess* taxonomy, Fig. 6.3, has been defined based on established standards (DIN8580) and realized in English language using a standardized translation.

The ManufacturingProcess ontology is one of the building blocks of an overarching, modular ontological framework. The vision of such a future modular framework of an industrial setting and its actual status is outlined in Fig. 6.4.

Emerging domain ontologies for *SensorSystems*, *ActuatorSystems*, *DataStreams* and *DigitalShadows* as currently developed in the CoE (Becker et al. 2021) will be integrated soon and complement the overall ontological framework. Especially the MaterialOntology will be further connected to the numerous relevant domain ontologies like a MicrostructureOntology, a CrystallographicOntology, and many others already introduced in the section on material ontologies. Eventually this

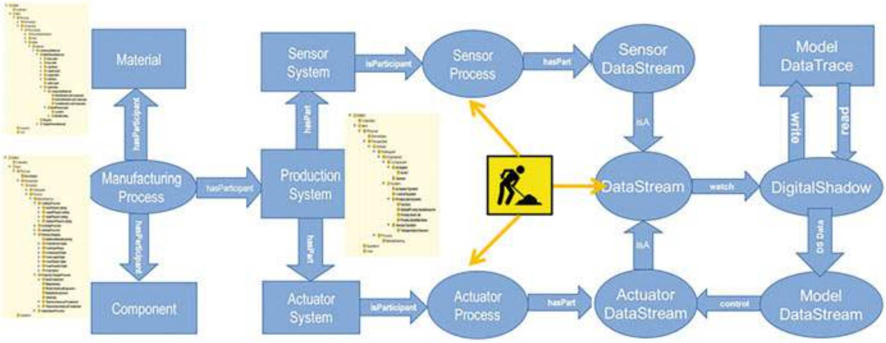

Fig. 6.4 Modular configurable system of domain ontologies for an industrial setting. Squares denote the ontological description of a state, while ellipsoidals represent ontological descriptions of processes. The arrows indicate ontological relations based on mereology and mereotopology (Casati and Varzi 1999; Schmitz 2020, 2022). Processes havePart other processes (e.g., SensorProcess hasPart SensorDataStream) and have participants, which are states (e.g., SensorProcess hasParticipant SensorSystem). The cream-colored ontology screenshots indicate the currently available taxonomies/ontologies

will allow to link production process data to material property data and vice versa. The modular ontological framework then will allow to also include further domain ontologies like production planning, logistics, business, and finance and many more.

6.6 Simulation Platforms

Once interoperability between a variety of models and data is obtained there is a chance for the realization of integrating workflows allowing the description of materials and components along their entire production and service life-cycle. The major requirements for a "simulation platform" are: (i) suitable and available hardware (e.g., cloud, grid, HPC), (ii) a comprehensive set of relevant and modular configurable software, (iii) a workload manager, and (iv) a workflow orchestrator. In case commercial codes or proprietary data are involved there is a further need for (v) a user and access rights management and eventually for (vi) back office solutions, e.g., for accounting purposes.

Quite a number of simulation platforms are nowadays available, Fig. 6.5, with a number of them being harmonized and integrated into a metaplatform being currently under development in the MarketPlace project (MarketPlace 2022).

Work within the Cluster of Excellence in this area has been focused on AixViPMaP, which is based on a first concept for an ICME simulation platform addressing process chains being proposed about a decade ago (Schmitz and Prahl 2012). The AixViPMaP platform since then has significantly matured and now is operational for microstructure simulation workflows adaptable to different metallic systems and process conditions (Koschmieder et al. 2019).

Fig. 6.5 Currently known open simulation platforms (DGM 2022). Open in this context means the backbone of the platform to be opensource resp. open access and contrasts to commercial platforms like 3D experience or Ansys workbench

Workflows on AixViPMaP (and also on many other platforms) are orchestrated by Jupyter notebooks invoking software modules of different classes: “Creators” serve to generate an initial virtual material state and may also comprise experimental data. “Evolvers” advance this state according to process conditions. “Extractors” eventually calculate properties from a state, while not altering it. The material state data is stored in a HDF5 file being consecutively updated with new data throughout the workflow eventually leading to a full description of a microstructure at given conditions. AixViPMaP (www.aixvipmap.de) can be run either in the cloud or on a grid with the workload distribution being controlled by a HT Condor middleware. Essentially the AixViPMaP is software agnostic and thus basically all types of software can be run, with the minimum requirement being a batch execution capability. Integrated Computational Materials Engineering (ICME) is characterized by application and combination of multiple simulation software tools and a variety of data. A respective cloud-based infrastructure comprising dedicated commercial and open access simulation tools has successfully been used not only for first research projects but also already during an interactive online training/education event (Koschmieder et al. 2021).

6.7 Conclusion

By the use of Integrated Computational Materials Engineering (ICME) a digital twin of the material or component can be derived. By combining the digital twin with in process data and machine learning it is possible to conceive a digital materials shadow. By the use Integrated Structural Health Engineering (ISHE) the health state of components can be monitored during their entire life cycle to avoid failures and enable timely replacement. To enable communication between humans and machines, it is necessary to create a strictly defined language in the form of ontologies.

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Material Solutions to Increase the Information Density in Mold-Based Production Systems

7

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Abstract

Production processes for the manufacturing of technical components are enabled by the availability and use of adequate engineering materials. Within the Internet of Production this work stream is dedicated to developing material and process-based solutions to increase the data availability during the manufacturing and operation of discontinuous mold-based production systems such as high-pressure die casting (HPDC) and injection molding (IM). This includes the development of data-driven alloy design strategies for additively manufactured mold components using tool steels as an initial use case as well as new surface-based smart sensor and actuator solutions. Material data and properties are tracked from the steel powder production via gas atomization until the final use in a mold to produce castings. Intermediate steps include the 3D printing of mold components via laser powder bed fusion and subsequent application of physical vapor deposition and thermal spraying-based smart multilayer coatings with sensor and actuator capabilities. The coating system is refined by selective laser patterning to facilitate the integration onto complex shape molding tool surfaces. Furthermore, molecular dynamics simulation-based methods are developed to derive material properties required for the modeling of polymer-based materials. By using this integrated methodology with the application of integrated computational materials engineering (ICME) methods from the metal powder for the mold printing up until the casting or molding process, the foundation for a holistic life cycle assessment within the integrated structural health engineering (ISHE) framework is laid for the produced tooling systems as well as the molded parts.

7.1 Introduction

Mold-based production systems are of high prevalence in the manufacturing industry due to their ability to facilitate the high-volume production of technical components from material classes such as non-ferrous alloys and polymers. High-pressure die casting as well as injection molding machines are highly automated production systems that can provide a wide range of data via their sensors and control systems, especially if the process data is available via state-of-the-art interfaces such as OPC UA. Most of the direct physical interaction however happens between the mold and the process material. Consequently, the mold and its manufacturing process must become a part of the data stream within the IoP by using adequate materials and material models during mold manufacturing and the mold usage cycle. Most hot work tool steel alloy compositions that are in use for permanent molds in these processes have been optimized for the classical production route via forging, milling, and consecutive heat treatment. With the increasing adaption of 3D metal printing and its specific thermal regime rapid development of optimized or new alloys via ICME methodologies is required to realize cost and performance goals. By capturing and storing the process data during metal powder atomization as well as the printing process the knowledge of local microstructural defects that negatively impact the properties of the mold component can be leveraged to drive ISHE-based methods to better assess the state of the mold during the usage cycle where thermal and tribo-chemical wear can occur. A key requirement to apply ICME calculations to predict the microstructural features of a cast alloy is the availability of precise information about the conditions at the mold interface to assign adequate boundary conditions for the simulation. In order to provide the required boundary conditions thin multilayer coating-based smart sensors and actuators produced by means of physical vapor deposition and thermal spraying are under development to increase the availability of data and to control the process temperature at the interface between the melt and the mold. The multilayer sensor coating system is structured by selective localized laser ablation of specific layers to enable localized functionality on AM manufactured and conventionally manufactured molds. Process data is collected for the coating as well as the laser ablation procedure to improve the sensor manufacturing process and to provide the data basis to facilitate ISHE assessments during the usage cycle of the mold. By addressing the key challenges of new material solutions for the tooling itself as well as increasing the availability of data from the mold-melt interface two crucial steps toward enabling ISHE and ICME for the mold-based production route are taken. Consequently, the digital description of the molding material itself is the remaining challenge to be overcome to facilitate ISHE and ICME from the tool steel powder until the final product from the materials engineering perspective. Molecular dynamics simulations are integrated into the IoP framework to increase the availability of material data for improved ISHE assessments of the molded part.

7.2 Powder and Alloy Development for Additive Manufacturing

Material properties of technical components must be tailored to suit specific application requirements. In conventional processing, materials are typically made to undergo multi-stage heat treatments resulting in customized microstructures. Such processes are characterized by the presence of multi-phases and their associated formation temperatures. However, a similar approach is not easily transferable to the domain of additive manufacturing (AM) due to the manifestation of metastable conditions resulting from different temperature profiles and often leading to poor component properties through defects. Therefore, a new approach to AM process-based solutions is crucial in designing materials with tailored microstructures and predictable properties that fit specific application requirements. The approach must be data-centric, where data from both the material design process and online sensor-based measurement systems can be effectively extracted and transformed into structured and semi-structured databases with advanced querying capabilities. Subsequently, such databases can be combined with data science and AI-based approaches to analyze and exploit the optimization potentials of AM processes. Such analyses can be used to draw process-specific correlations, track material information over time, integrate predictive capabilities into the AM process chain to draw conclusions about the material microstructure and predict failures (the ISHE concept) during the product life cycle, and the computational development of alloys (the ICME concept).

Laser powder bed fusion (LPBF) is an additive manufacturing process based on the layer-wise production in a powder bed and the selective melting of the powder by means of a laser beam. Cooling rates in LPBF typically lie between 10^6 and 10^7 K/s. Investigations of LPBF manufacturability of hot work tool steels (HWTS) are limited so far, in some cases with contradictory results in microstructure-property correlations (Casati et al. 2018; Huber et al. 2019). In this work, a holistic methodology for modifying HWTS for increased LPBF-manufacturability is demonstrated with a standard 1.2343 HWTS for a mold based high-pressure die casting (HPDC) production system. First, LPBF process parameters are developed for the standard 1.2343 alloy. In the second step, the alloy composition is adapted based on the experimental results of step one to increase manufacturability. Alloy development via research scale powder atomization and blending enables the rapid production of new alloys for AM in research quantities. Alloy development has traditionally been an iterative, time- and resource-consuming process due to the constant need for remelting, casting, and testing new alloy compositions (Koss et al. 2021). Since in most LPBF processes, pre-alloyed powders are applied, another time- and energy-consuming step of atomizing metal powders follows (Ewald et al. 2019). Our team of researchers has therefore investigated the use and proven the feasibility of powder blends (mixtures of pre-alloyed and/or elemental powders) in the context of rapid alloy development for high manganese steels (Ewald et al. 2021) and high entropy alloys (Ewald et al. 2019; Kies et al. 2020).

The amount of metal powder needed can further be reduced by switching to manufacturing processes with local powder supply: in situ mixing of powders allows rapid changes between alloy compositions and the fabrication of graded samples (Koss et al. 2021). One of these processes is extreme high-speed laser material deposition (EHLA), a technology originally developed for coating applications which has evolved to a 3D printing technology (Schaible et al. 2021). Using EHLA, more than 300 different alloy compositions can be manufactured easily within one workday. EHLA process parameters can be controlled in such a way that the dendrite arm spacing is comparable to LPBF manufactured components (Koss et al. 2021). This is an important feature in the context of alloy development for LPBF, since mechanical properties are foremost influenced by microstructure which in turn depends on the chemical composition and solidification conditions such as cooling rates (Koss et al. 2021). First unpublished investigations on 1.2343 and a modification of 1.2343 show comparable DAS values in LPBF and EHLA samples. Throughout the alloy development process (Fig. 7.1), data is collected in all steps, starting with powder atomization, including powder characterization,

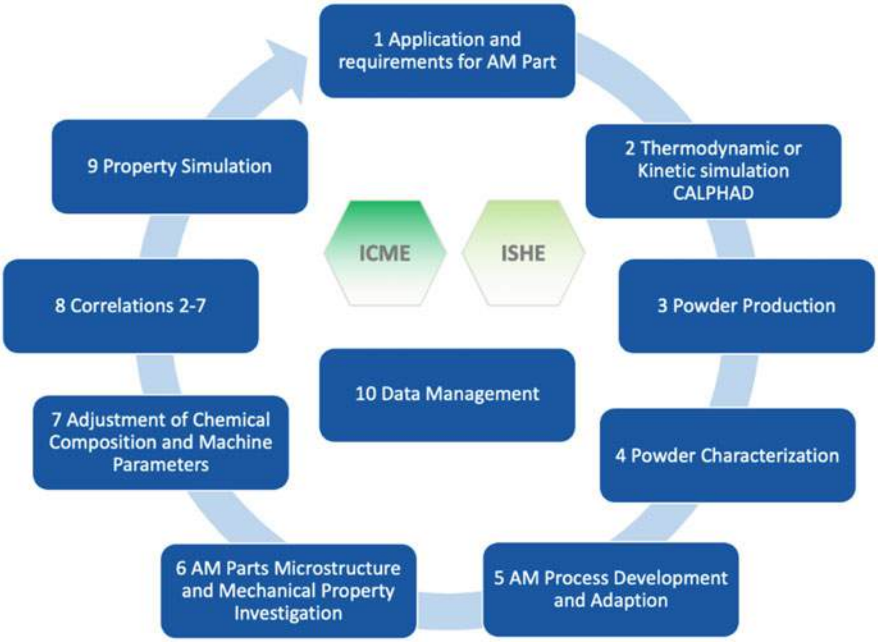

Fig. 7.1 Holistic material development cycle

continuing with LPBF/EHLA manufacturing, and concluding with the investigation of microstructure and properties of the final component. The data is basis for the analysis of process-material correlations to allow process optimization and predictive microstructure and property modeling. All raw data is gathered in a data lake which acts as a central hub. The effective assimilation and restructuring of this raw data enable the development of material databases, cross-platform interfaces, and inter-workstream operability. These form the basis of ICME and ISHE (integrated structural health engineering) property prediction, the improvement of material design, and the creation of digital shadows.

Cycle 1 – Standard composition: 1–6 → 10

1–3: The HWTS 1.2343 was chosen for the application and required properties, TC phase simulation was done, the powder produced, and all data stored.

4: The atomized powder was qualified for further usage in the process chain: chemical composition, shape, and particle size distribution (PSD). The powder microstructural phases were determined and quantified: martensite, 5% retained austenite (Fig. 7.2a).

5 and 6: The alloy was LPBF-printed with different print parameters. The different microstructures and properties were investigated. For the standard steel 1.2343, a heating plate (T = 500 °C) was necessary to reduce the amount of retained austenite (RA) in the martensitic matrix from 18% to max. 1,1% (Fig. 7.2b, c).

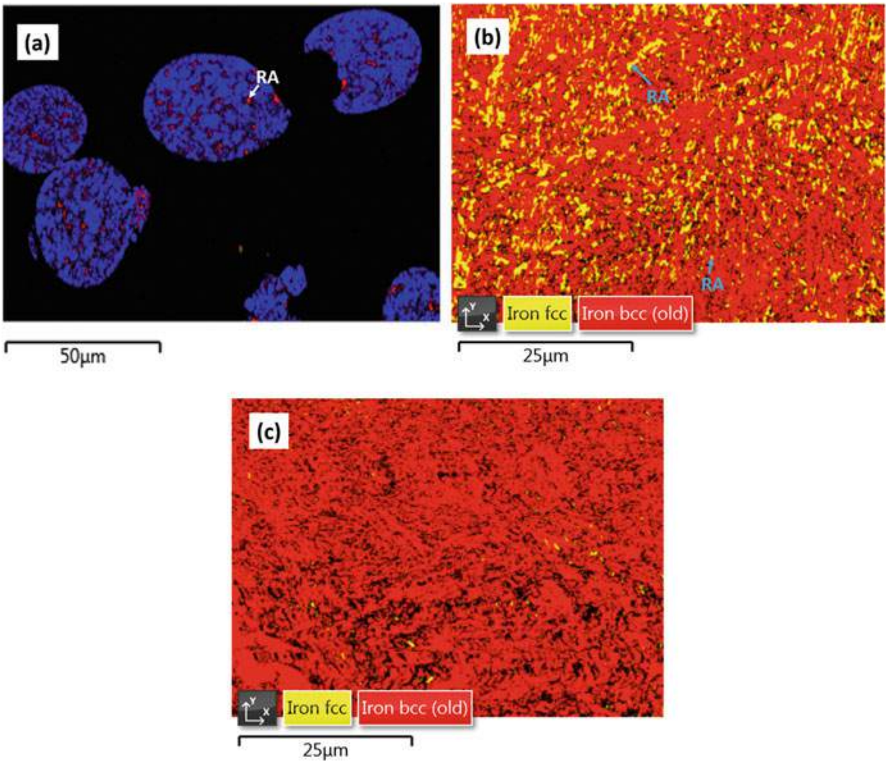

Fig. 7.2 EBSD-images of 1.2343 Standard (**a**) powder particle with ca. 5% RA (red), (**b**) as built without preheating with ca. 18% RA (yellow), (**c**) with preheating at 500 °C

Cycle 2 –Modified composition: 7, 2–6 → 10

7, 2–6: Based on findings and data gathered from 1 to 6, alloy modification was necessary with the goal to create a steel with less RA through a combination of carbon and strong carbide formers as well as solid solution strengthening alloying elements. To facilitate alloy modification and new compositional design, Calculation of phase diagrams (CALPHAD) based simulations were helpful in microstructure phases prediction (2). Based on the new modification, the alloy can either be produced via atomization or blending (3) and characterized (4). In the modification, the standard composition was adapted to the process (5). The microstructure was evaluated (grain size, cell sizes, shapes, cell boundary structures, carbides, segregations, martensitic, austenitic phases) and the mechanical properties of the printed parts with and without heat treatment were tested (6). In this modified as-built condition, no RA was found.

Correlations and property simulations: 10 → 8, 9 → 10

8: Comparison and correlations of both the steels, in terms of microstructure and mechanical properties were performed.
9: Subsequent steps would involve the simulation of material properties, the ISHE usage, and the determination of correlations among process variables.

The concept of alloy development via AM powder route supports the increased adoption of 3D printing of mold components for HPDC or IM. The main results showed that the preheated standard steel achieved the maximum strength without a second annealing treatment and that the modified steel reached its maximum strength results without a preheat treatment, both industrial benefits (Raffeis et al. 2022). Data gathered during the process chain were vital in controlling and customizing microstructures for the required property applications. The material and process data gathered along the process chain form a solid basis which shows a clear pathway for further computational alloy development leading to an alloy composition validated for manufacturing a mold for HPDC and successive smart multilayer coatings application onto the mold surface.

7.3 Smart Coatings

The temperature is an important parameter in manufacturing technology to influence tool performance and lifetime, properties of the workpiece, and energy consumption for manufacturing. For monitoring and controlling the process temperature, the data from the direct interface between mold and workpiece or mold and melt is necessary. For this purpose, a smart multilayer sensor-actor-coating-system was developed. This temperature sensor coating was deposited by means of physical vapor deposition (PVD) and combined with an actor heater coating deposited by means of thermal spraying (TS). PVD is a vacuum process. A solid target material can be transferred into gas phase by sputtering with inert gas ions, such as argon or krypton. The particles in the gas phase accelerate to the substrate, such as tools for aluminum die casting, on which the coating growth takes place. By utilization of reactive gases, such as oxygen or nitrogen, hard coatings can be deposited (Bobzin 2013). The basic principle of thermal spraying is that a feedstock material is melted with the aid of a thermal energy source (Lugscheider and Bach 2002). Subsequently, this is accelerated onto the substrate surface via an atomizing gas in the form of spray particles. On impact with the surface, which has previously been prepared and activated by blasting, the particles are flattened and solidified immediately. A coating is formed due to the overlapping of particles.

The two coating processes PVD and TS enable the deposition of coatings for the interface between mold and alumium melt. Furthermore, the deposition of the

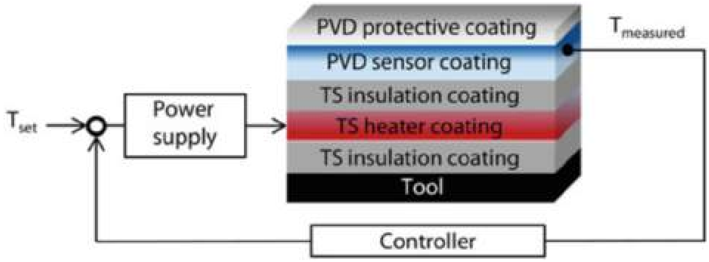

Fig. 7.3 Schematic structure of a temperature control circuit consisting of PVD temperature sensor coating and TS heater coating

required functional coatings is implemented. The schematic structure of a coating for temperature control is shown in Fig. 7.3. It composes of insulation as well as functional coatings. The electrical insulation coatings serve an electrical shielding of the functional coatings from other metallic, electrically conductive components, such as the steel tool or the molten aluminum. A further insulation coating is applied between the functional coatings to prevent electrical interference between the different principles for the sensor and actor function. The insulation top coating is in direct contact with the environment and has a protective function against wear and other stresses. The functional coatings are divided into a measuring PVD sensor and a heating TS actor coating. The measuring function, based on the operating principle of the thermoelectric effect, requires a material combination that exhibits characteristic potential differences at different temperatures (Körtvélyessy 1998). The material combination is implemented by deposition of two coatings, overlapping at the measurement position and separated at the contact positions, for measuring the differences in potential. The actuator function is based on the generation of heat on the principle of Joule heating. The metallic TS heater coating acts as a resistance heater and converts supplied electrical energy into thermal energy due to the specific electrical resistance.

The PVD sensor coating combines the function of temperature measurement with wear resistance. Metallic and nitride sensor coating variants were developed for this purpose. The nitride (Cr,Al)N + (Ti,Al)N sensor coating integrates the temperature sensing property into this protective function (Bobzin et al. 2021a). The metallic Ni + NiCr sensor coating generates a resolved potential difference, which is also used in calibrated type K thermocouples for precise temperature measurement. In combination with an aluminum oxide top insulation coating, a suitable resistance in tribological contact was provided, protecting the underlying sensor functionality (Bobzin et al. 2021b). The combination of metallic and ceramic coatings leads to the risk of an eggshell effect. Due to the reduced mechanical resistance of the metallic coatings, cracking or delamination of the insulation coating can result and affect the function of the sensor coating. The metallic sensor coatings should be applied thin to increase the ratio of wear-resistant insulation coatings to metallic coatings and to enable temperature measurement at the direct interface. Therefore, the influence of the coating thickness on the temperature measurement by means of the metallic PVD sensor coating was considered. The parameters for deposition of the PVD sensor coatings are shown in Bobzin et al. (2021b). The coating thickness was adjusted by varying the coating time, while the other parameters were not changed. For the Ni and NiCr coatings, the deposition times $t_A = 23.75$ min for coating A, $t_B = 47.50$ min for coating B, and $t_C = 95.00$ min for coating C were varied to consider the sensor function depending on the coating thickness. The sensor function was checked by temperature measurement during the heating process in comparison to reference measurements of a calibrated type K thermocouple. The results are shown in Fig. 7.4. The calibrated thermocouple, blue, and the PVD sensor coatings A, B, and C showed an approximately constant increase in temperature up to $t = 200$ s. At $t > 200$ s the temperature control of the heating element started. The measured temperature of the calibrated thermocouple initially decreased because of convective heat transfer and readjusts with the regulation. The measured temperatures of the PVD sensor coatings were higher than the temperatures measured with the calibrated thermocouple. The temperature measurements of the PVD sensor coatings A, B, and C showed negligible differences compared to each other. The standard deviation of the individual measurements was smaller for the PVD sensor coatings compared to the calibrated thermocouple. There was good reproducibility of the measurement results regardless of the coating thickness. Accordingly, these thin PVD sensor coatings can be used in technical processes independently of the coating thickness.

Premature solidification and cold shuts of the aluminum alloy due to long flow paths in narrow sections can be prevented by an increase in the surface temperature. The TS actor coating can be used for variothermal temperature control of the cavity in die casting. In this way, the heat exchange at the interface between mold and melt can be directly influenced. The TS actor coating developed consists of several layers. A bond coating was applied to the mold, which ensures that the subsequent

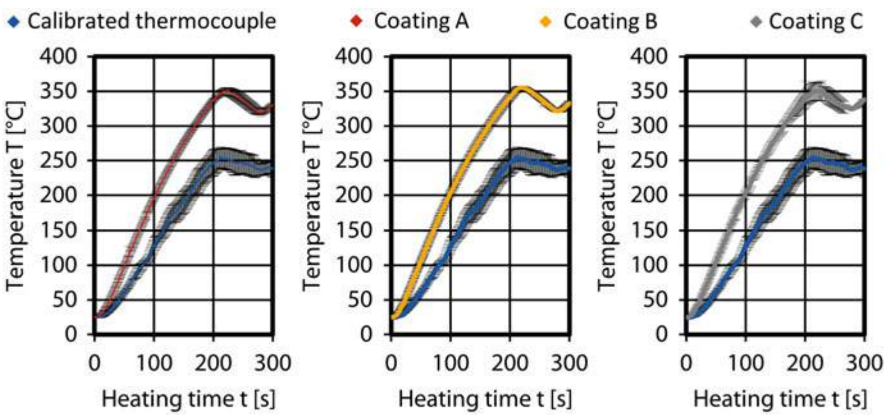

Fig. 7.4 Temperature measurement by PVD sensor coatings A, B, and C

layers adhere. For electrical insulation, the NiCr20 heater coating was surrounded by two ceramic Al_2O_3 coatings (Bobzin et al. 2021c). The applied heater coating enabled the component surface to be heated to several 100 °C. Due to the low electrical resistivity of NiCr20, the heater coating was applied in a meandering path and with a low coating thickness in order to achieve a higher electrical resistance and thus a sufficient heating power. Figure 7.5 shows a thermographic image of the heated actor coating. Up to now, heating rates of up to 10 K/s were achieved and temperatures of T = 350 °C were reached.

Both, the PVD temperature sensor coating and the TS actor coating, are functional and suitable for use in technical applications. The combination of the two coatings is the next step. Figure 7.6 shows a cross-fracture image of the combination of the metallic Ni + NiCr coatings on a TS insulation coating by scanning electron microscopy (SEM). The metallic coatings showed a columnar structure. The transition between the measuring metallic coatings was hardly visible and a suitable electrical contact for the formation of the thermoelectric effect

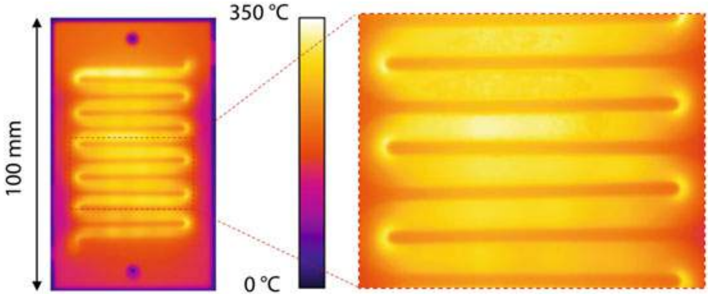

Fig. 7.5 Thermographic image of active TS actor coating

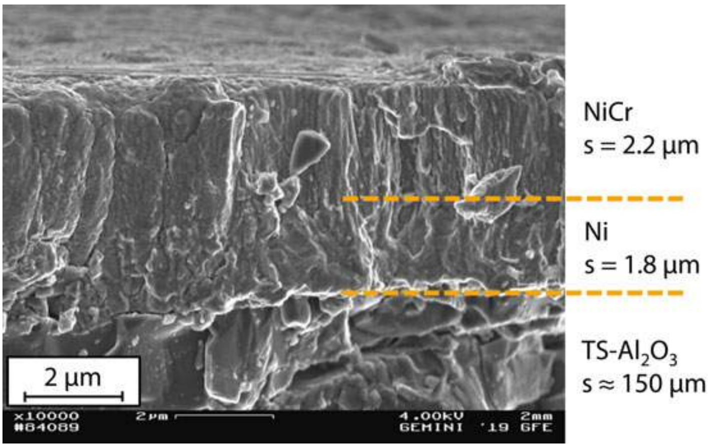

Fig. 7.6 PVD Ni + NiCr sensor on TS insulation coating in SEM cross-fraction

was assumed. No discernible gap formation between the metallic coatings and the TS insulating coating was visible. This suggests a suitable adhesion within the temperature control system. By means of the two surface technology processes, temperature monitoring and control can be implemented directly at the interface between mold and melt or between mold and workpiece. This allows an increased reliability of the mold as well as an increased component quality to be achieved.

The existing PVD sensor coating should be extended for spatially resolved measurements and the application on complex geometries. On complex geometries, masking is challenging for shaping of the contacting and measuring points. The structuring of the multilayer coating system requires a selective ablation of individual coatings without affecting the coatings underneath. In particular, the ablation of similar coatings such as the measuring sensor coatings Ni and NiCr has to be controlled and monitored precisely in the nanometer range. In this context, the extension of laser ablation offers a promising possibility, which needs to be further researched. The TS heater coating should be further improved and the heating rate increased. This can be accomplished by using a stronger power supply or increasing the electrical resistance of the heater coating through a finer meander structure. For this purpose, laser structuring can be a possibility to enable precise structuring of the heater coating.

7.4 Laser Ablation

Laser ablation is a versatile tool for thin film patterning, especially on freeform surfaces as in the present case for smart heater and sensor coatings (Fig. 7.7). Laser thin film patterning is used for different materials: transparent or opaque – dielectrics, polymers, or metals; a vast range of film and substrate material combinations is possible. The selective ablation is achieved by one of these methods: Either the processed layer is more susceptible to laser irradiation than the layer or substrate below or the laser process parameters are tuned in a trial and error method with intermediate ex-situ determination of the ablation depth and atomic composition in the ablation area. In the present case, the first method is not applicable because the threshold fluences of Ni- and NiCr-layers are identical (0.11 J/cm^2). The second method is tedious and relies on the constancy of the layer thickness. However, this assumption may fail for three-dimensional surfaces where the film deposition rate depends on local geometry features (Fig. 7.7).

Thus, we aim to measure locally and in-situ the atomic composition, identifying the currently ablated layer. Areas which have not reached the target layer are further processed. Ergo, a closed-loop control system is formed. Moreover, the gained process data is further enriched with subsequent ex-situ measurements, geometry information and data from previous process steps as depicted in Fig. 7.8. The ultimate goal is the training of an artificial intelligence (AI) with the former data. The AI is trained to optimize the laser process parameters a-priori. Laser-induced breakdown spectroscopy (LIBS) is utilized for in-situ material detection. Optical breakdown (i.e., ablation) and subsequent plasma formation of the material

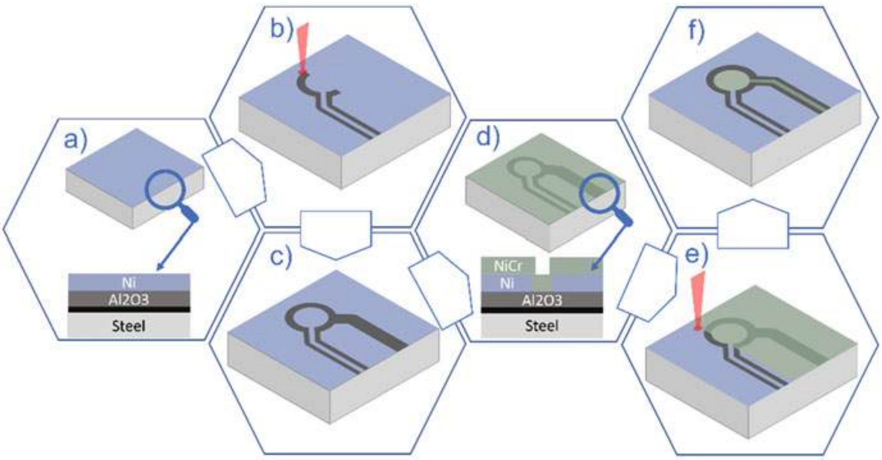

Fig. 7.7 The interplay between laser ablation and PVD coating. (**a**) The steel substrate is PVD coated with an interlay, Al_2O_3, and Ni. (**b**) Selective laser ablation of Ni to form an isolated path. (**c**) Resulting ablation pattern. (**d**) PVD coating with NiCr. (**e**) Laser ablation of NiCr. (**f**) The finished thin film sensor with a Ni and a NiCr conductor, which meet at one point to form a sensor

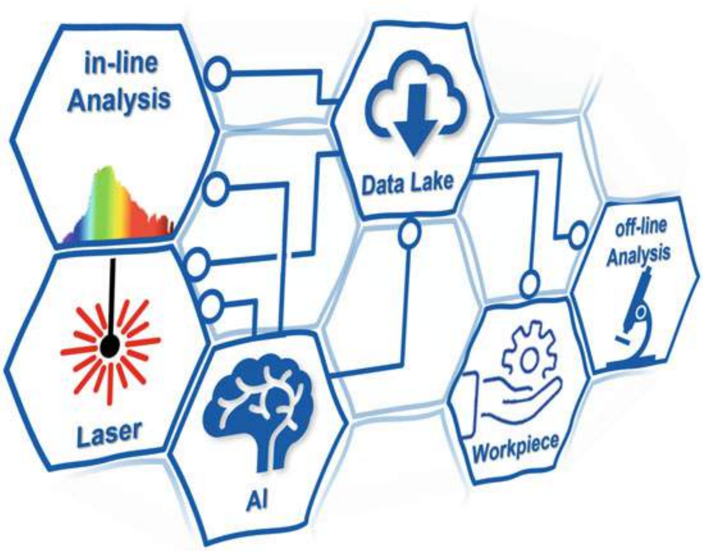

Fig. 7.8 The distributed laser process, consisting of a classical laser process, which forms a closed loop control in conjunction with an in-situ analysis. An artificial intelligence (AI), which a-priori plans the process, is constantly trained by new available data. The data is enriched by ex-situ measurements and data from the workpiece itself, such as the surface profile or the film deposition parameters. The backbone of the distributed process is a NoSQL database

are achieved by laser irradiation. The excited atoms and ions in the plasma emit characteristic line radiation (Noll 2012). LIBS has been used successfully for thin film characterization as well as depth sensing for multi-layer systems, even for sub-micrometer layer thicknesses (Nagy et al. 2017; Cabalín et al. 2011; Owens 2011).

In this work, the depth sensing capabilities of LIBS for the present film system, the two-dimensional resolution of the LIBS spectra as well as the selectivity of the ablation have been characterized. The ablation thresholds of all materials have been determined by Liu's method (1982). The film system is already described in Sect. 7.3. The depth of the ablated areas was measured with a laser scanning microscope (VK9700, Keyence) and the element ratios were determined by electron dispersive X-ray spectroscopy (EDX, Oxford Xray Detector System).

A clean ablation without damage of the isolation layer Al_2O_3 could be achieved. Even though well below the ablation threshold of Al_2O_3, the isolation layer was damaged for a fluence of 0.6 J/cm^2. The damage is attributed to spallation, induced by excessive heating of the underlying, highly absorptive TiAlN interlayer. This finding further confirms that a spatially resolved detection of the material composition is crucial for an efficient, selective process. Even a small deviation in the film thickness of Ni or NiCr could result in a damage of the isolation layer.

The depth sensing capabilities of LIBS were explored with three different methods. First, a spectrometer (HR2000+, OceanOptics) as a sensing device (He et al. 2020). The drawback of the spectrometer is its slow acquisition time of 1 ms as compared to usual laser pulse-to-pulse differences of ca. 1–10 μs. Second, a single fast photodiode was utilized. The transition from Ni to Al_2O_3 and then to steel could be determined by both methods after two and three passes. EDX was used to determine if the respective layer was completely removed. Both previous methods lack the ability to assign a signal to its spatial origin. The third method aims to overcome these drawbacks. The photodiode signal and the laser scanner (intelliScan 14 de, ScanLab) were acquired simultaneously by a custom field programmable gate array. The layer transition could be determined by all methods. However, the element composition could not be spatially resolved for the third method. Only an average difference was detected.

In conclusion, the possibility of an in-situ layer detection was shown. However, the signal needs to be spatially resolved. For that purpose, two more photodiodes will be implemented. All photodiodes will be equipped with different gauss filters, detecting single, strong emission lines of Ni, Al, and Cr. Moreover, a NoSQL database was set up and all laser parameters, ex-situ measurements, such as EDX and depth analyses, as well as the in-situ results are automatically uploaded and linked to each other. In that way all data will be at the disposal for training a deep neural network AI.

7.5 Molecular Dynamics for Digital Representation of Polymers

Plastics as polymer materials have a very wide range of properties, which can vary greatly depending on the type of polymer used. This very broad spectrum of properties leads to a high degree of complexity regarding processing and usage (Dahlmann et al. 2022). To counteract this complexity and to represent the plastic in the sense of ICME and ISHE in the cluster of excellence, the goal is to represent the polymer as a digital material and investigate in it virtually.

As Fig. 7.9 shows, the goal is to represent the plastic as a digital material, starting from its synthesis, through processing, its use in the life cycle, and the end of its lifetime by means of simulations on various scales.

In all the above stages, the complex properties of the plastic are partly or entirely determined by its molecular structure (Dahlmann et al. 2022). A simulative description of the material at the atomic level helps to represent the polymer's respectively the plastic's properties as a digital material. One important method for atomistic simulation is molecular dynamics (MD) simulation. This method relies on distributing a certain number of particles in a usually cube-shaped box. The interactions between the particles are usually described by pair potentials and their summation (Haberlandt et al. 2012).

In polyamides, the thermal properties are influenced by the corresponding water content (Batzer and Kreibich 1981). These influences can be described by MD

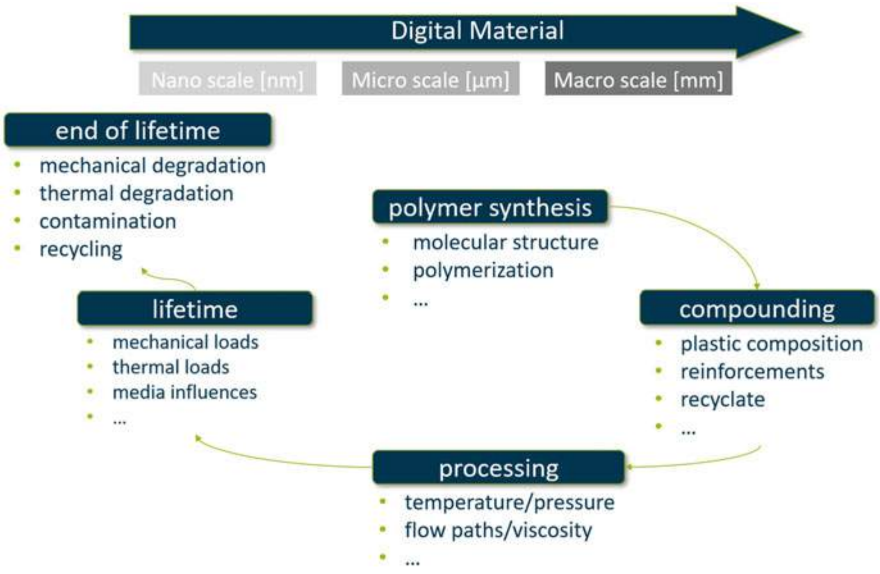

Fig. 7.9 Illustration of the plastic material throughout its complete lifecycle

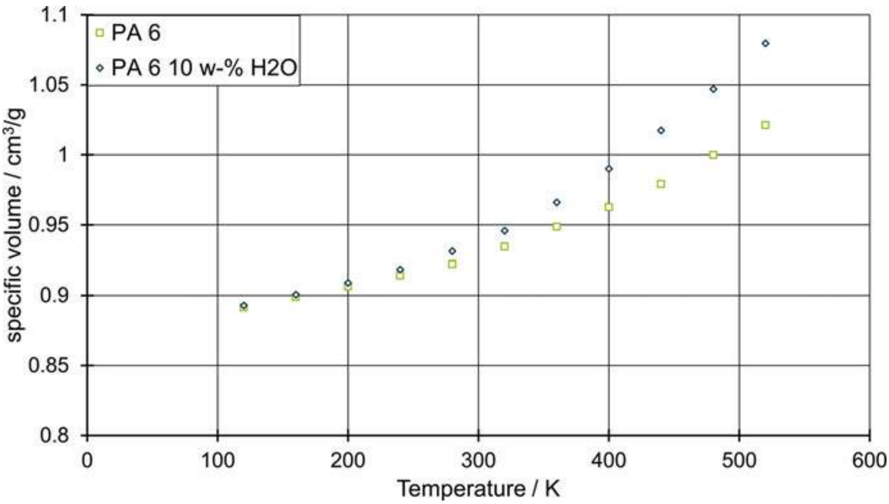

Fig. 7.10 Plotting the specific volume against temperature to investigate thermal properties of PA6 with different amounts of water uptake

simulations and thus allow their prediction. For this purpose, calculations were carried out on a dry PA6 and a PA6 saturated with 10% by weight.

As Fig. 7.10 shows, the changes in thermal behavior due to water uptake can be described, at least qualitatively, by the MD simulations. Further MD simulations were used to investigate the plastic processing, especially the process of foaming. For the modeling of the foaming process diffusion coefficients are needed which were determined by MD simulations (Melzer et al. 2022). Thus, the digital representation of the plastic material helps reduce experimental effort and reduces the needed resources. On this way plastic processing can be optimized, and sustainability is increased.

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Toward Holistic Digital Material Description During Press-Hardening

8

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Contents

Abstract

Press hardening of manganese-boron steels is one of the most widely used production processes for high-strength automotive components. The low residual formability of these parts is a decisive disadvantage. The low formability originates from a strong, but brittle martensitic microstructure transformed

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during quenching in the press-hardening tool. In contrast, medium manganese steels (MMnS) contain high fractions of ductile retained austenite improving press-hardened parts toward promising candidates for crash-relevant car body components. Disadvantages include a more complex alloy design, a highly sensitive production process, and more demanding requirements on the tool due to higher strength during press-hardening.

A detailed description of the entire production process along the process chain including the material and the press-hardening tool is important for tailoring the properties. Combined information is required to enable a precise control of the production process and its influences on the final properties of the part. Maximum economic use of the material is achieved by digitally describing MMnS as well as the tool along the entire process chain (casting, forging, hot rolling, cold rolling, galvanizing and press hardening including Q&P). To link the process steps and to describe the changes of the material, a new material database structure (idCarl) was developed. All production parameters are recorded and processed as a digital material twin. Ultimately, deviations occurring during production process can be deduced from in-line data analysis and counteracted. These can then be counteracted by adapted process control and the product can be brought back into the required parameter field of properties. Clear identification of the component and the used material allows conclusions about steps responsible for errors in the production process that become apparent during use.

8.1 Introduction

Producing high-strength press-hardened components is complex, imposing high demands on the material but equally on the press-hardening tools. Interconnected production processes for press-hardening influence each other and provide a complex interplay between material and production tools. Capturing microstructural parameters can be understood as key to understand this complex interplay. In the context of Internet of Production (IoP) the material description constitutes a bridging between the various production technologies.

In contrast to conventional alloy concepts for press hardening parts, Medium-Manganese-Steels (MMnS), a relatively new steel grade, offer promising improvements of the final properties of components produced. In order to ensure that these beneficial properties can be transferred to relevant industrial use cases such as b-pillar production, the material must be able to tolerate the necessary forming operation without material failure during manufacturing. Consequently, the material undergoes a number of treatment steps before press-hardening (casting, forging, hot- and cold-rolling, and galvanizing) that affect the microstructure. During press-hardening a precisely controlled interplay of the microstructure and the process parameters is of highest importance to achieve consistent and high-quality output. To achieve these goals, a cross-process chain description of materials was developed that captures and links all materials encountered in the process. In order to describe the process chain, it is necessary to analyze the individual process steps, to transfer the relevant parameters into a data-based form and to link them with each other. In the following, individual steps of the process chain have been highlighted. The individual chapters deal with:

- Digital description of the material for press-hardening and the database structures set up for this purpose
- The digitalization of the material behavior during deformation and improvements to achieve optimal properties
- Digitalized press-hardening tools and their additive manufacturing
- Data-driven material description of press-hardening tools in the form of representative volume elements

8.2 Digital Description of Material for Press-Hardening

Since its introduction, *Digital Twin* has drawn the attention of both industry and scientific field and has been researched and applied in numerous fields (Qi and Tao 2018; Fuller et al. 2020; Liu et al. 2019; Boschert and Rosen 2016; He et al. 2019). The digital twin was defined as a digital representation of its physical counterpart (Grieves 2015), which can be physical object, system, or process. However, implementation of the Digital Twin in practice is barely feasible due to its requirement of massive amount of data and complexity of description models, which is also impossible to deploy for monitoring and prediction purpose for production in real time. Therefore, in IOP, the *Digital Shadow* is proposed as a light version of the Digital Twin, meaning that it is "a set of contextual datatraces and their aggregation and abstraction collected concerning a system for a specific purpose with respect to the original system" (Becker et al. 2021) and represents only a particular aspect of the real object (Brauner et al. 2022). Thus, digital shadows provide a reduced amount of data sets as compared to digital twins, but capable of describing a system's state and history for a certain purpose and, therefore, make the deployment of the *Digital Shadow* in real production feasible.

However, materials are so far barely mentioned during the digitalization of production processes. Therefore, two new concepts for material digital description, *Digital Material Twin* for material state description and *Digital Material Shadow* for material processing, are proposed. In the present investigation, the focus is set on the digital description of material current state solution (Digital Material Shadow) with examples and a concept is proposed on the Digital Material Shadow for Press-Hardening.

Firstly, one workpiece is described as a collection of intrinsic and extrinsic properties. An extrinsic property can be a shape, roughness, or stiffness of a workpiece, which is the reflection of the material property, but not material property itself. With intrinsic or material-inherent properties (e.g., chemical composition, yield strength), however, the material characteristic can be completely presented. Thus, intrinsic properties of materials are defined as components for the Digital

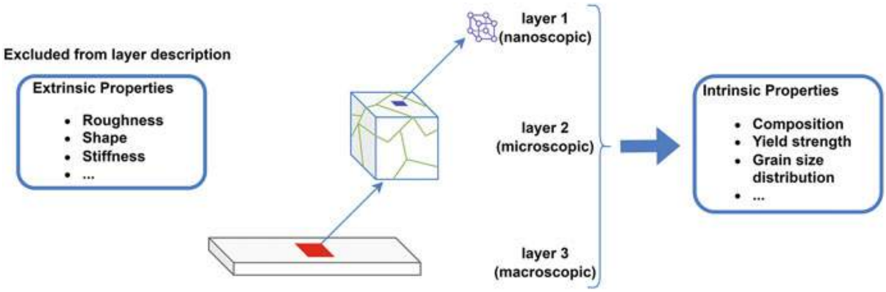

Fig. 8.1 Three-layer description of the Digital Material Twin

Material Twin. Here, we divide intrinsic properties into three layers: nanoscopic (layer 1), microscopic (layer 2), and macroscopic (layer 3). Layer 1 describes the material from atomic point of view, in which the crystal structure and the crystal defects, distribution, and diffusion of foreign atoms are described, whereas layer 2 describes phase and microstructural characteristics of material, e.g., phase fraction. In layer 3, the statistical summary (e.g., UTS, yield strength) of all the units of layer 2 will be presented. With the intrinsic properties and 3-layer description, a comprehensive Digital Material Twin can be deployed (Fig. 8.1).

Moreover, the Digital Material Twin description is extended by its correlated process step since the material state change along the process chain. With extended Digital Material Twin, each material state description can be connected and presented as a digital processing chain for one material.

Furthermore, for IoP, four components are of interest for implementing the approach into the IoP infrastructure: *Smart Human Interfaces*, *Model-Integrated AI*, *Data Modelling*, and *interconnected Infrastructure* (Brauner et al. 2022). Thus, with the concept of Digital Material Twin, a containerized Web Application with the name *intelligent digital Computational advanced research laboratory* (idCarl) is developed and deployed within the IoP. The structure of idCarl is presented in Fig. 8.2. In this approach, researchers have the possibility to create a Digital Material Twin with its chemical composition, and the extension of the Digital Material Twin (process step with core parameters). The information of the Digital Material Twin is stored in each *material card*, along with predefined, user-depended, unique *Material ID*. The information of the Digital Material Twin extension will then be stored in a *treatment card* with its *Treatment ID*. For the subsequent *material card*, the *Material ID* of its previous material state will also be stored, so that the material state can be described in chain. With the defined *Material ID*, users can also append subsequent or previous processes for expansion of the processing chain. Moreover, within the idCarl structure, a *material card* is considered as a node for testing data input and realize the *interconnected infrastructure* (Brauner et al. 2022). The user can initially test the material state with the testing machine, and the key value will then be retrieved with the designed app from the raw data output file from the machine and stored into designated *material card*. Currently, the key value of material state,

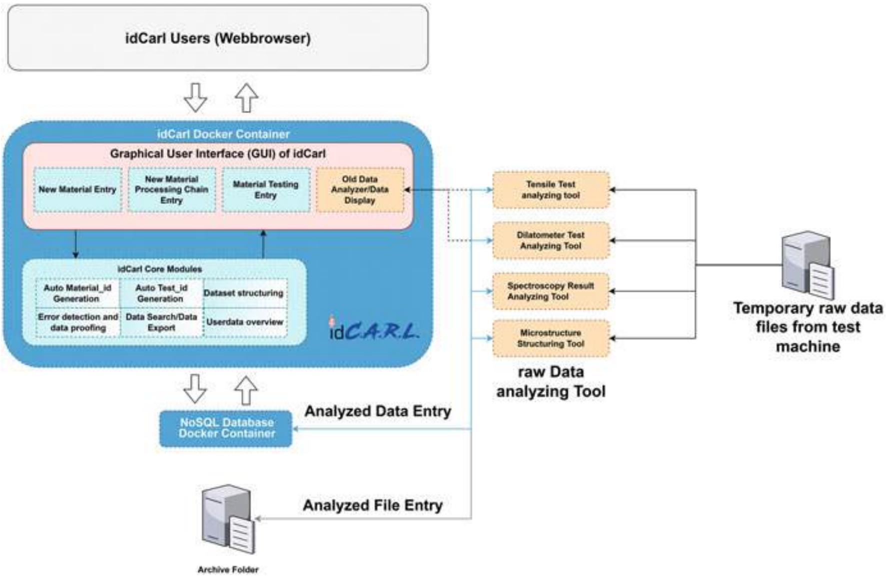

Fig. 8.2 Schematic representation of the organizational structure of idCarl and its essential components

e.g., chemical composition (with optical emission spectrometer, OES), ultimate tensile strength, yield strength and Young's modulus (with tensile machine), and martensitic start and finish transformation temperatures (with dilatometer), which represent the third layer in Digital Material Twin structure (Fig. 8.1), can be stored in a database with the developed tool box.

Since the deployment of idCarl and its core database – MongoDB is based on the concept containerization, the decentralized web application idCarl can be deployed on various platforms or operation systems which support Docker, with configuration to designated NoSQL Database Container. Moreover, with the containerization solution, further data analyzing models, data processing models, or physical models can then be appended to the idCarl structure, which also expands the functionality of idCarl and provides a comprehensive three-layer Digital Material Twin.

Moreover, the core concept of IoP is based on the Digital Shadow, which is defined as a reduced model/model collection for processing from a specific aspect in real-time.

One example of applying idCarl in the IoP is the press-hardening process. For press-hardening as use case, the development of mechanical properties, e.g., yield strength, ultimate tensile strength, and phase transformation temperatures along the process chain, from casted material to press-hardened component, are of great interest to identify necessary (real time) adjustments of subsequent process steps. Therefore, the structured datasets within idCarl, models for description of target intrinsic property and parameters correlation (see Fig. 8.3), and data collected from sensors will be applied for the *Digital Material Shadow* development. The Digital

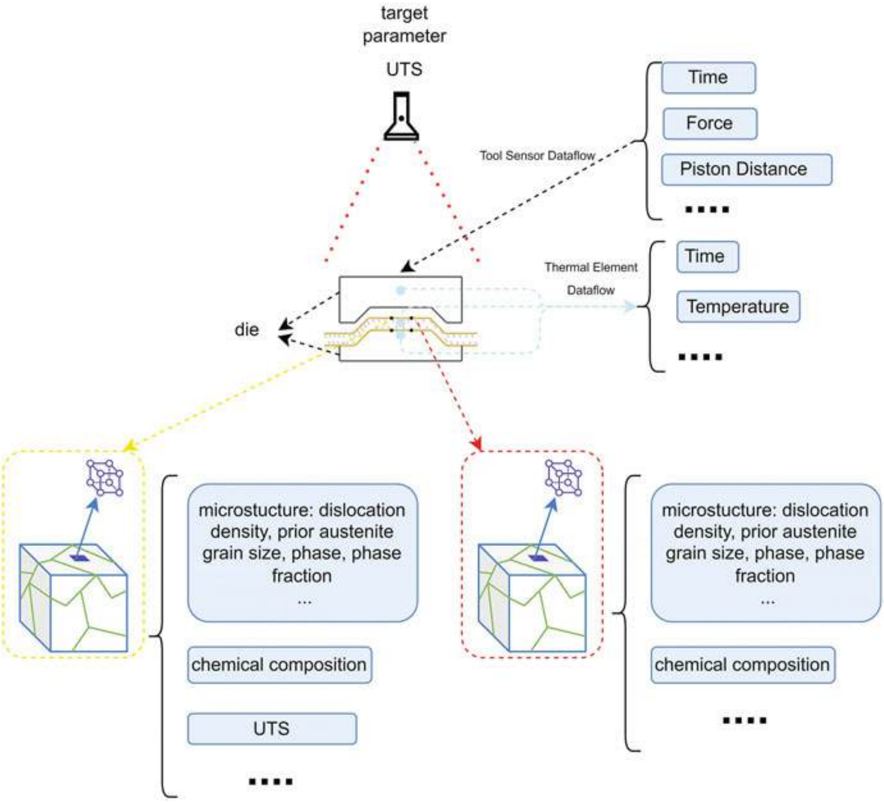

Fig. 8.3 Schematic illustration of the Digital Material Shadow of press hardening: target property monitoring through reduced extended Digital Material Twin and dataflow collected by sensors

Material Shadow can then be applied for target property monitoring and prediction along with the press-hardening process. With containerized approaches of *Digital Material Shadow* of MMnS for press-hardening, a *worker pod* or even *worker node* which contains relevant containers can be established with selected Container Orchestration tools (e.g., *Kubernetes*) into the IoP framework.

The description and monitoring of the built-up process chain of press-hardening of MMnS in the IOP begins with sheet material production including melting of the material, hot rolling, soft annealing, and cold rolling. After melting, the chemical composition of every ingot is analyzed by OES and stored into its *Material Card.* Additionally, for every above-mentioned process step a subsequent *Material ID* and related unique *Treatment ID* with most important treatment parameter, like type of treatment (e.g., hot rolling, cold rolling, heat treatment), deformation grade, deformation rate as well as temperature and time, is generated. Following each process step, the material is tested by tensile testing and investigated by dilatometry. The resulting third layer intrinsic properties are stored into the corresponding

Material Card using associated apps. The development of the characteristic values along the process chain can be displayed by a tree view in idCarl whereby necessary process adjustments of the subsequent process steps can be easily identified. For example, from the detected brittleness of a specific hot-rolled material, idCarl may recommend the need for soft annealing before cold rolling. A suitable annealing temperature could be defined on the basis of the in idCarl stored phase transformation temperatures from dilatometer experiments.

To improve mechanical property combinations of high strength and high residual forming capacity of press-hardened MMnS components, the performed press-hardening process was extended by an integration of quenching and partitioning (Q&P) treatment. Instead of quenching to room temperature after pressing, the material is quenched to a temperature between martensite start and martensite finish temperature, provided by idCarl. Given that martensitic transformation is not completed, retained austenite can be stabilized by subsequent partitioning. Hence, this heat treatment leads to a combination of soft (austenitic) and hard (martensitic) microstructural components to be set sensitively by Q&P parameters, especially quenching temperature, partitioning temperature, and partitioning time (Blankart et al. 2021; Edmonds et al. 2006).

As the phase fractions strongly influence the mechanical properties, accurate temperature control and monitoring during press-hardening and Q&P process is essential (Yang and Bhadeshia 2009; Clément et al. 2015). Since cooling is performed in the closed tempered press hardening tool, various thermocouples were integrated onto the tool and work piece to monitor the current component's temperature in real time. Time for opening the tool and transferring the work piece to the partitioning furnace is always tracked. In case of handling problems the desired properties can still be achieved within certain limits by extending the scheduled partitioning time (Clément et al. 2015; Blankart et al. 2021). For these real-time process adjustments, a fast estimation of the resulting second layer properties depending on the Q&P parameters is required. Based on dilatometric data of cold rolled material, an empirical approach in accordance with Koistinen-Marburger equation was developed for the here investigated Fe-0.3%C-5%Mn-1.5%Si MMnS and can be used to estimate rapidly the austenite fraction and hence martensite phase fractions (Blankart et al. 2021). Additional apps to store surface pressure force and pressing time into idCarl is going to be developed shortly as well as an app for saving Q&P parameter out of measured time-temperature raw data.

8.3 Digitalization of Material Behavior During Deformation

During press hardening, sheet metal forming operations, such as deep drawing or stretch forming, formability of the material plays a major role when assessing the suitability for its use in this forming process. The materials formability characterizes its ability to tolerate plastic deformation without the creation of defects like fractures or excessive thinning. A Forming Limit Curve diagram (FLC), schematically shown in Fig. 8.4, is often used to assess a materials formability. The FLC displays the

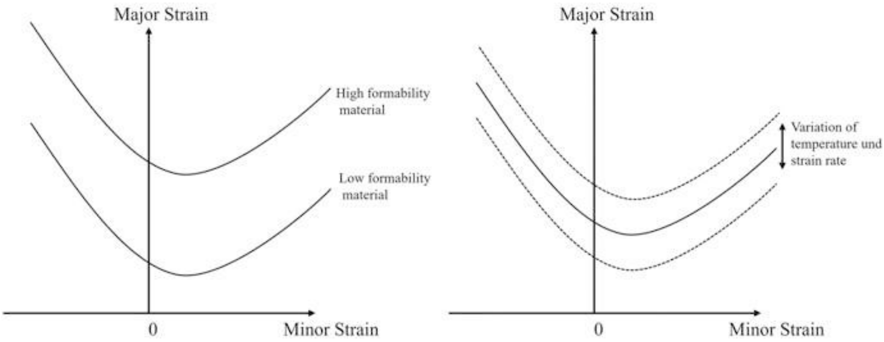

Fig. 8.4 Schematic example of a forming limit curve

point of material failure for different ratios of major and minor strains. A material's formability is therefore higher when greater strains can be tolerated before failure. As the forming during press hardening takes place at elevated temperatures, the formability is also affected by processing temperature and strain rate (Karbasian and Tekkaya 2010).

While testing methods for FLC determination are well established for cold forming conditions, for example, Nakajima testing, methods usable for hot stamping conditions are currently only investigated (Mori et al. 2017).

As can be seen from the FLC, a press hardening process can only be assumed to be robust in term of formability if the strains occurring in the formed component sufficiently lower than the strains leading to failure according the FLC. The design of the pressing tool and therefore the magnitude of strains and ratio of major and minor strains are mostly predetermined by the desired geometry of the finished product. As the geometry of press hardened components, for example in the automotive application, is strongly dependent on the overall chassis design, there is little possibility to adapt the process to compensate for an insufficient formability of the processed material. The choice of a suitable initial sheet geometry can optimize the material flow during forming and reduce the risk of material failure.

To assess the formability of the material designed in the use case a press hardening tool for manufacturing a miniaturized b-pillar is used. Figure 8.2 shows the influence of the initial sheet geometry on the manufacturability of a simplified b-pillar part. Figure 8.5 (a) shows an overlay of the two different sheet geometries along the symmetry axis of the sheet. Figure 8.5 (b) shows the result of a finite element analysis using the software *AutoForm.* Again, the results of the two sheet geometries are overlaid along the symmetry axis. The geometry presented on the left side results in material flow during forming that causes excessive thinning in the top and bottom part of the b-pillar walls. The calculated thinning exceeds values of −0.25, therefore the occurrence of cracks during press hardening is very likely. In comparison the geometry presented on the right shows a more complex sheet geometry design that results in optimized material flow and no cracks are expected according to the

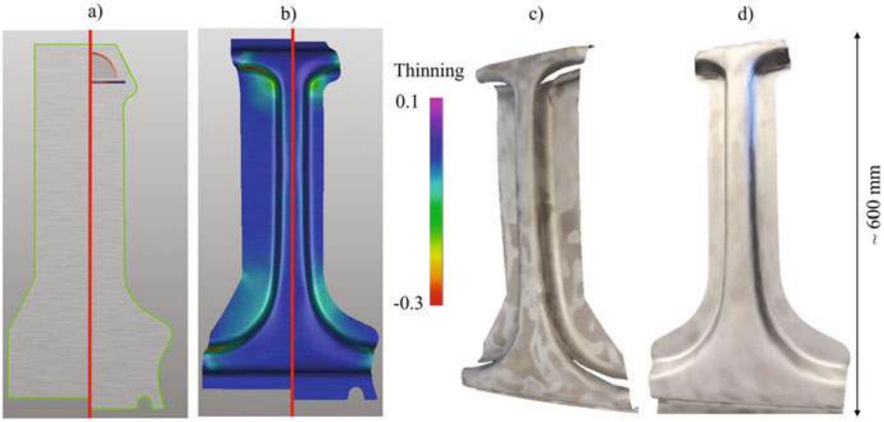

Fig. 8.5 Influence of initial sheet geometry on material failure during forming

simulation result. Figure 8.5 (c) and (d) shows the produced b-pillars for both sheet geometries. In the experiment the material displays the expected behavior and cracks occur for the simple sheet geometry on the left side. The complex sheet geometry results in a defect free part. Using an optimized sheet geometry, the influence of a suboptimal sheet geometry on the occurring forming limits of the process can be reduced. Therefore, the influence of material inherent formability is easier to investigate when conducting experiments using the b-pillar tool.

As mentioned, the determination of an FLC for the press hardening process is currently not standardized. As a first method of assessing the material formability hot tensile tests are performed. The resulting values for uniform elongation and maximum elongation are used to approximate the formability of different material batches that pass the process chain.

To correlate the results of the formability assessment to the chemical composition and parameters of previous processing steps along the process chain presented in the use case press hardening data received from FEA (predicted maximum thinning, strain distribution at points of maximum thinning), hot tensile tests (uniform elongation, maximum elongation) and experimental b-pillar production (machine force/displacement, measurement of sheet thickness after forming) are aggregated in json format and stored in a document-oriented database (Fig. 8.6). This data can then be integrated into the idCarl environment.

8.4 Digitalized Press-Hardening Tool

To form the sheets during press hardening new tools need to be developed to meet the increasing demands for individualized cooling channels and complex geometries that can be achieved by additive manufacturing. Additive manufacturing of metals is a production technology that involves manufacturing tools to form metallic

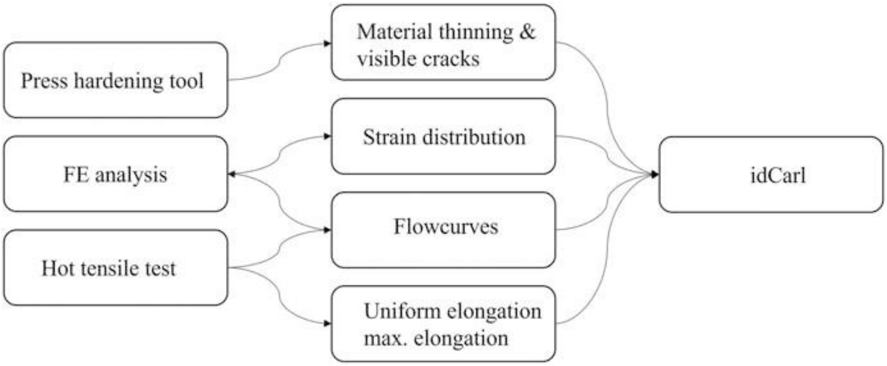

Fig. 8.6 Data transfer of formability experiments, simulation, and b-pillar production to the idCarl environment

materials layer-by-layer. The Laser Powder Bed Fusion (LPBF) process is one of the most industrially relevant additive manufacturing processes, where the component is built up with thin layers of powder by a laser. The LPBF process combines digital design and high freedom of manufacturing, which opens the possibility for new product-functionality and reduces the process chain for development. The main current applications of this technology involve medicine (Javaid and Haleem 2018), aviation and aerospace (Gisario et al. 2019), and automotive (Chantzis et al. 2020).

In industry, creating tooling requires fast product development, low cost, and high efficiency. To meet these challenges and requirements, additive manufacturing as rather novel technology has been applied and developed, which provides the potential to revolutionize completely the process of manufacturing (Rosochowski and Matuszak 2000). Opposed to conventional subtractive manufacturing, additive manufacturing possesses advantages, e.g., production of complex geometries, low material waste, flexible design, and low tooling costs.

We proposed an integrated digital process chain for the process optimization of the tools with the help of the material database idCarl, as illustrated in Fig. 8.7. The data infrastructure is organized: the data from each step in the manufacturing line are collected. The data collection procedure can be performed either manually using human-machine interface or automatically by different sensors. With these sensors, it is possible to monitor the process in real-time. The abundant data realize a detailed process description. After the data acquisition, the data will be processed firstly by idCarl database. Then the data will be analyzed and implemented to simulation for the process optimization.

The production and application of the Press Hardening (PH) tool is an excellent good example of the above process chain. Press tools and molds are commonly designed with internal cooling channels. Conventional manufacturing methods, such as drilling or casting, have the challenge that the cooling channels cannot follow the best designed geometry, which is normally in complex shape (Chantzis et al. 2020).

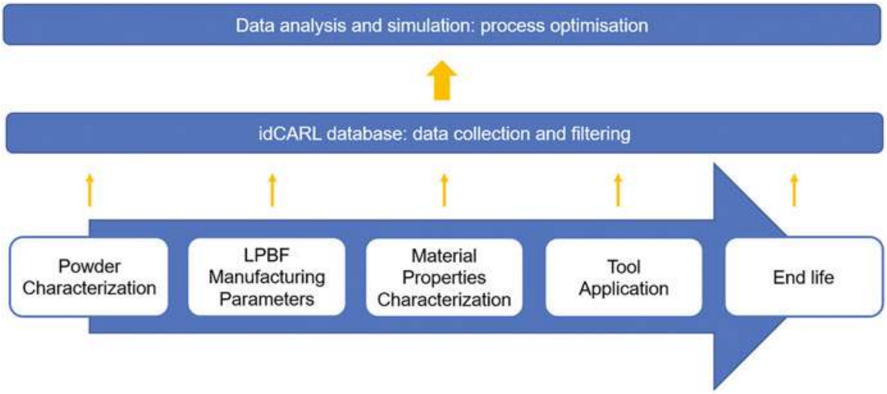

Fig. 8.7 Data infrastructure for the integrated digital process chain of a powder metallurgy (PM) tool production

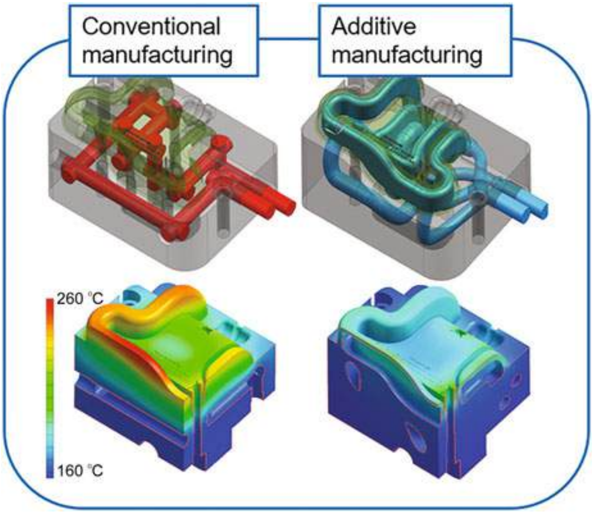

Fig. 8.8 The comparison of temperature distribution of tools produced by conventional manufacturing and additive manufacturing. The conformal cooling channels realized by additive manufacturing decreases the thermal gradient and leads to a better temperature distribution on the tool surface. (Adapted from https://www.plasticstoday.com/injection-molding/milacrons-dme-partners-linear-ams-develop-3d-printed-conformal-cooling-technology)

LPBF provides flexibility for designers that is unachievable under conventional manufacturing methods, especially for the tools that will not be massively produced.

The production of press hardening tools by LPBF exemplifies one implementation of AM for tooling production. The press hardening integrates the forming and quenching into one step for producing high-strength automobile body panels (Neugebauer et al. 2012). AM enables the new design of conformal cooling channels of the PH tools, which cannot be manufactured by conventional methods. These conformal cooling channels improve the cooling efficiency, and as a result, the manufacturing cycle time of PH process is reduced and the quality of products is enhanced (Hoffmann et al. 2007). Figure 8.8 illustrates how conformal cooling channels produced by AM can optimize the temperature distribution.

Overall, the manufacturing of tools by AM is one of the incorporating elements of Industry 4.0 and Internet of Production (IoP). AM contributes to the smart factories through customization and topology optimization, which are limited by conventional manufacturing systems (Dilberoglu et al. 2017). On the other hand, AM shortens the optimization and development procedure. In the process chain, every step can be monitored for data collection in order to achieve instant feedback, continuous optimization, and traceability of the whole life cycle (Moshiri et al. 2020).

8.5 Data-Driven Material Description of Press-Hardening Tools

For the accompaniment of the process chain through means of digital shadows/twins, several parameters must be analyzed and characterized. Our goal is to digitally replicate the microstructure of the final press hardening tool to allow such characterization. This is done via so-called statistically representative volume elements (sRVE). With the help of these sRVE the influence of different microstructures, and thus different manufacturing parameters can be examined. Specifically, the influence of voids or inclusions can be examined by the application of the sRVE. Firstly, it is mandatory to achieve an extremely close statistical representation of the material in question and the microstructure that is aimed at. This step is particularly important, as later steps aim at estimating a realistic microstructure representation using only process parameters as input. Thus, the statistical description of the parameters needed to characterize the microstructure, such as grain size or grain elongation need to be done with attention to detail.

Commonly, statistical procedures to describe a materials' microstructural parameters employ simple histograms, to which distribution functions are fitted (Fig. 8.9). There are, however, two key issues with this practice: For histograms, the continuous parameters are put into buckets which can be shifted in size, which in turn significantly alters the resulting distribution function. It is therefore a lot more accurate to apply Kernel Density Estimations (KDE) to these statistical descriptions.

The second key problem is that the histograms and distribution functions are created separately from all other parameters. Thus, these parameters are not interconnected. However, the parameters of the microstructure are commonly interdependent as was shown in a study (Pütz et al. 2020). In the same study the fitting solution to this issue was presented with the application of a deep learning method. For this method input data was collected from multiple microstructure analyses in the form of data sheets where the grain sizes, the grain shapes, and the grain orientations in relation to the rolling direction were collected. This set of data was subsequently applied as the input data of a deep learning approach, called Wasserstein generative adversarial network. This approach pits two networks

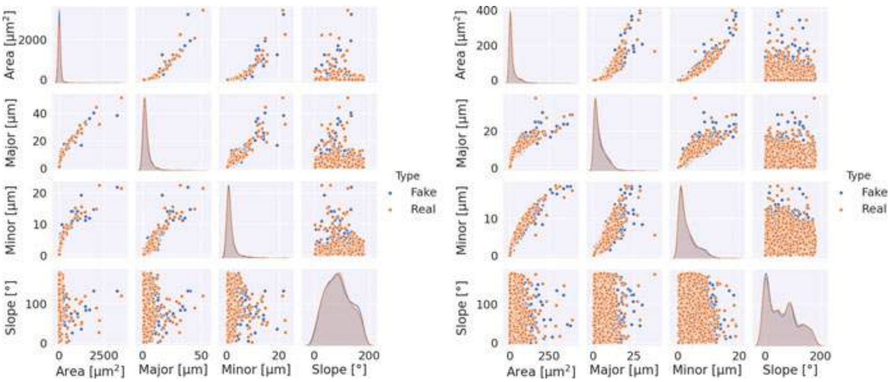

Fig. 8.9 Comparison of microstructure features (left) and inclusion features (right). (From: Fehlemann et al. 2021).

against each other, where one generates data that resembles the input data as closely as possible, while the other learns to distinguish real data from generated. Via the competition of these networks, the generator network improves significantly and is able to reproduce not only the statistical distributions of singular microstructural features, such as grain size, but also the present interdependencies.

Further extensions made to this deep learning approach changed the loss function to include a gradient penalty. Additionally, a conditional part was added to train multiple features with the same network (N. Fehlemann et al.). This is especially important for the implementation of inclusions to the network. Inclusions are a predefined breaking point, especially during cyclic loading which is present for the press hardening tool. Thus, the characterization of the inclusions is equally important to maintain the representativeness of the overall virtual microstructure. In Fig. 8.1 a trained deep learning so-called CWGAN-GP (Conditional Wasserstein generative adversarial network with gradient penalty) network can be seen. In this network, the relevant parameters of both the steel phase and the inclusions were trained within the same architecture.

The trained network then returns a virtual unlimited amount of unique input data that could all be present in the real microstructure. With the help of these extremely close statistical representations and a novel sRVE generator that utilizes discrete generation and grain growth (Henrich et al. 2020), very realistic microstructure representations can be created (Fig. 8.10). When load paths from real applications are applied to these virtual microstructures, the effect of the microstructure on the material properties can be closely examined. This leads to a quantitative estimation of the influence of individual features on the properties of the whole material and can in turn be used to make sure the produced part's quality lies within the required performance range.

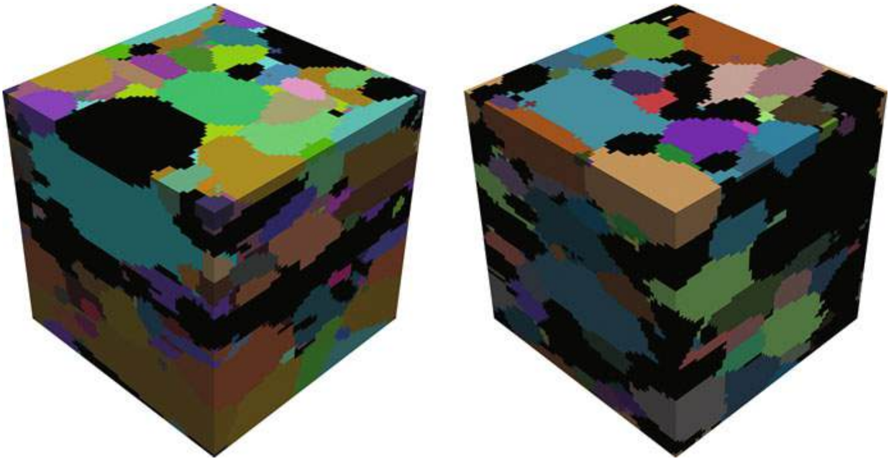

Fig. 8.10 Generated sRVE that show different microstructure features and complexities

8.6 Conclusions

Within this chapter we further developed the previously introduced concepts of digital twin and digital shadow toward Digital Material Twin for material state description and Digital Material Shadow for material processing. These were applied to the press-hardening process of steel, where we identified medium manganese steels (MMnS) as a promising candidate to surpass the mechanical properties of conventionally used manganese-boron steels. We introduced idCarl, a web application for describing material changes on different length-scales along the process chain. Only with tracking these changes in dependence of processing parameters, e.g., on the microstructural level, the full potential of relatively unexploited alloys as MMnS for press-hardening can be reached. We provide an underlying database structure for the digital description and process behavior of (i) materials during press-hardening and (ii) materials for additively manufactured press-hardening tools. For the latter, a data-driven 3D microstructure generator was described providing realistic representative volume elements. Information extracted from introduced digital material shadows enables the identification of in-line production errors and thus allows direct measures of (real time) process adjustment during press-hardening.

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Materials in the Drive Chain – Modeling Materials for the Internet of Production

9

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Abstract

In this chapter, the focus lies on a predictive description of the material response to the thermomechanical loads within different process steps by means of physical and data-driven models. The modeling approaches are demonstrated in examples of innovative production technologies for components of a drive chain: Fine blanking of parts; powder metallurgical (PM) production of gears; open-die forging and machining of drive shafts. In fine blanking, material, process, and quality data are acquired to model interactions between process and material with data-driven methods. Interpretable machine learning is utilized to non-destructively characterize the initial material state, enabling an optimization of process parameters for a given material state in the long-term. The PM process chain of the gear includes sintering, pressing, surface densification, case hardening, and finishing by grinding. Several modeling and characterization approaches are applied to quantitatively describe the microstructure evolutions in terms of porosity during sintering, density profile after cold rolling, hardness and residual stresses after heat treating and grinding and the tooth root load bearing capacity. In the example of the open-die forging, a knowledge-based approach is developed to support the decision-making process regarding the choice of the proper material and optimized pass schedules. Considering the microstructure of the forged shaft, the elastoplastic material behavior is described by a dislocation-based, multiscale modeling approach. On this basis, process simulations could be carried out to predict the process forces, chip form, residual stresses, and the tool life among other output data.

9.1 Introduction

In the Cluster of Excellence "Internet of Production" at the RWTH Aachen University, a research domain is dedicated to materials. The main objective of this research domain is to provide digital tools to design dynamic production scenarios and condition-based monitoring of components, based on the knowledge about the material and components' properties. To this end, data are integrated from production and usage into physical and data-driven material models and digital material shadows are generated. This chapter contains three different process

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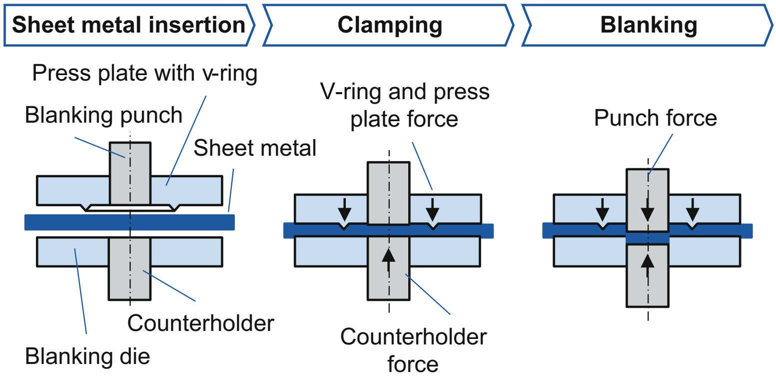


Fig. 9.1 Process steps in fine blanking

chains, chosen to demonstrate different approaches for modeling the materials in manufacturing processes within the context of the integrated computational materials engineering (ICME) and integrated structural health engineering (ISHE).

9.1.1 Fine Blanking

Fine blanking is a sheet metal shearing process. Compared to conventional blanking, fine blanking is characterized by a high geometric accuracy and a smooth shearing surface with only small tear-off (Aravind et al. 2021; Bergs et al. 2020). Fine blanking is used in mass productions of parts, e.g., for the automotive or aerospace industry (Pennekamp et al. 2019). Figure 9.1 depicts steps of the fine blanking process. First, the sheet metal is inserted into the tool. Next, the sheet metal is clamped between a press plate with a v-ring and a cutting die. Finally, the blanking takes place, before the blanked workpiece is ejected.

Despite the high precision of fine blanking, practitioners observe fluctuations in workpiece quality for fixed process parameters. These variations occur on batch level, but also along single sheet metal coils. For other sheet-metal processing manufacturing processes, research has already shown that deviations in product quality occur due to variations in material properties (Unterberg et al. 2021). A fine blanking line was equipped with sensors to capture material, process, and quality data to allow for a data-driven modeling of dependencies between material state, process state, and the resulting product quality in the long term (Niemietz et al. 2020).

9.1.2 High-Strength Sintered Gear

The powder metallurgical (PM) manufacturing of typical sintered gears usually includes powder preparation, e.g., by mixing a metal powder, pressing, and sintering

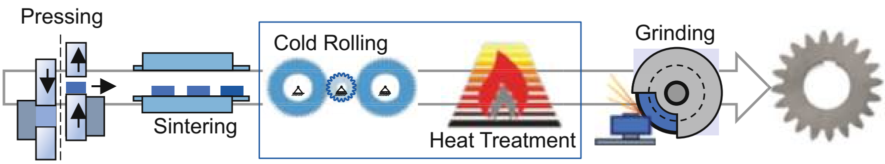


Fig. 9.2 Schematic representation of the PM process chain of high strength sintered gears

(Fig. 9.2). Some advantages of the PM route are the reduction of the material use and energy consumption in the production chain, flexibility in shape optimization, and better noise-vibration-harshness behavior of the gear (Kruzhanov and Arnhold 2012; Leupold et al. 2017). However, the strength of sintered gear is significantly lower than conventional gears, due to the remaining porosity after sintering. Further mechanical and thermal post-treatments are required, if highly loaded applications are considered for the sintered gear. Studies have shown that surface-densified and case-hardened sintered gears can achieve comparable levels of the load-bearing capacity of conventional gears (Gräser et al. 2014; Kotthoff 2003). Different modeling and simulation methods are carried out to study the process-material relation, aiming at an optimized process design for improved performance. The processes of sintering, case hardening, and grinding are highlighted in the following sections.

9.1.3 Drive Shaft

A drive shaft is a highly stressed component that is used in drive chains of various machines to transmit power and mechanical loads. In order to withstand the high, cyclical loads during their service life, the components must have excellent material properties. To this end, drive shafts, e.g., in vehicles, are often manufactured using a multi-stage production chain comprising hot forging, heat treatment, and (finish) machining (Zhao et al. 2019) (Fig. 9.3).

Despite the high level of standardization in modern manufacturing processes, hardly explainable fatigue events happen during the service life of highly loaded parts like axles or drive shafts in different machines like vehicles (Barbosa et al. 2011) or (bucket wheel) excavators (Savković et al. 2012). The reasons for these catastrophic failures, besides geometrical features, include defects regarding the local material properties like grain sizes and the surface integrity resulting from the individual manufacturing process chain (Zhao et al. 2019). To enable the tracking of the production process of individual components, a digital model of the production chain is created. Different methods including ICME-based material and process simulation approaches and knowledge-based systems are used to build a basis for developing a digital shadow that enables component-related assessments, e.g., on the unique service life (ISHE) in the long run.

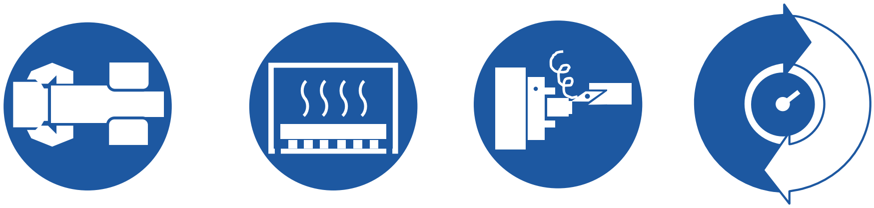


Fig. 9.3 Schematic representation of the process chain of a drive shaft

9.2 Fine Blanking – Artificial Intelligence (AI) for Sheet Metal Hardness Classification

As stated earlier, the quality of fine blanked parts varies, even without changing the process settings. Moreover, research has already shown that fluctuations in material properties lead to quality deviations in other sheet-metal processing manufacturing processes. If a digital shadow representing the actual properties of the material was available, it would provide a basis to develop an integrated model connecting material properties, process parameters, and quality parameters with the aim to adaptively control the fine blanking process based on a given material state.

One potential approach contributing to a digital material shadow is the so-called magnetic Barkhausen effect. Inside ferromagnetic materials are magnetic domains. These domains, which are separated by so-called domain walls, are regions in which the magnetic moments are aligned in one direction. When a time-dependent external magnetic field is applied to a ferromagnetic material, the domain walls move. However, the domain wall movement is hindered for example by dislocations, voids, or second-phase particles. Once the external magnetic field exceeds the restraining force of these obstacles, the domain walls break free causing jumps in the rate of magnetization of the ferromagnetic material (Jiles 2000). These Barkhausen jumps are measurable, e.g., with an inductive sensor. The resulting time series signal is called magnetic Barkhausen Noise (MBN). Due to its dependency on microstructural properties, the MBN is used for non-destructive material classification. The measurement of MBN is even fast enough to be applied in production lines (Franco et al. 2013).

Unterberg et al. (2021) conducted experiments on deep learning to classify the hardness of specimen from a 16MnCr5 (AISI: 5115) sheet-metal coil used for fine blanking based on MBN signals. They demonstrate that deep learning models, more precisely InceptionTime (Ismail Fawaz et al. 2020), allow to distinguish different classes of hardness. While deep learning is capable of learning complex relationships from raw data without manual feature engineering (Goodfellow et al. 2016), the inner complexity of artificial neural networks also renders their decision logic opaque to humans (Došilović et al. 2018). If models are only evaluated based on their prediction accuracy, it is unclear whether a model learned plausible relationships or just exploits misleading spurious correlations (Chattopadhyay et al. 2019). Moreover, potentially unknown (and correct) relationships learned by a model remain hidden from humans, preventing humans to learn from AI. Consequently, methods to interpret or explain machine-learning models (explainable AI) are required. Establishing explainable AI in manufacturing contributes to the vision of an Internet of Production, where every production step is seen as a potentially valuable experiment from which knowledge is gained.

Several explainable AI approaches, such as Grad-CAM (Selvaraju et al. 2020), explain model predictions by highlighting parts of the input data, which are most relevant to the prediction. However, such explanations leave much room for interpretation. For instance, if a region in an MBN signal is highlighted as being important, it is still ambiguous what properties (e.g., amplitudes, frequencies, peak values, peak positions, etc.) of that region are decisive for the model prediction. Li et al. (2018) propose an alternative approach. They present a neural network architecture and an objective function enabling to learn representative examples of the classes that are to be predicted by the model. The model derives its predictions based on similarity to these representative prototypes.

Experiments with an adapted version of Li et al.'s model architecture were conducted with the aim to classify the hardness of specimen from a 16MnCr15 fine blanking steel based on MBN measurements. Figure 9.4 depicts boxplots visualizing the hardness values of the used specimen, the final accuracies of the model for training data and validation data as well as learned prototypes. The hardness and the MBN were measured at eight different spots for each specimen. MBN signals were measured over a duration of 1 s at each spot, which were divided into subsignals with a length of approx. 3.3 ms as input for the neural network. For detailed information on the data acquisition refer to Unterberg et al. (2021).

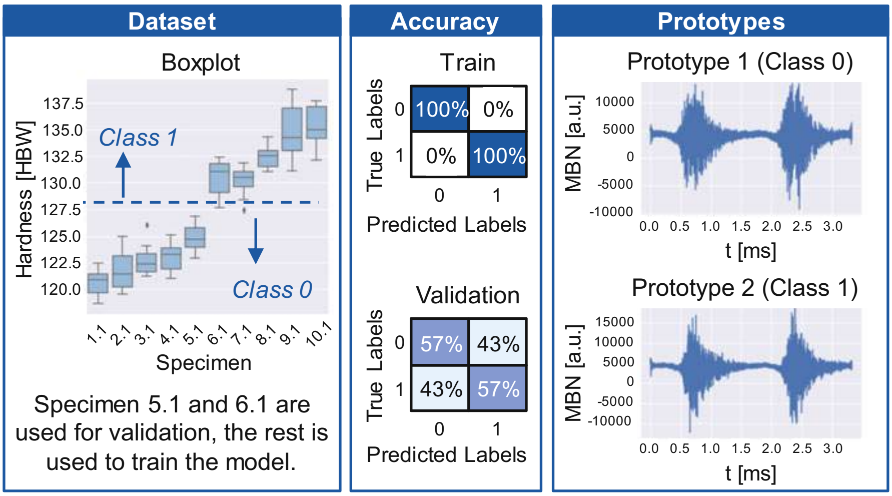


Fig. 9.4 Summary of experiments on interpretable hardness classification with deep learning

The reached validation accuracies are considerably lower than those of Unterberg et al. (2021). However, it becomes possible to compare the neural network's decision logic to existing domain knowledge, by checking whether the prototypes are consistent with findings reported in the literature on MBN. The learned prototypes appear to contradict relationships found in the literature. For instance, Franco et al. (2013) report that the peak height of the MBN decreases with increasing hardness. The prototypes suggest the opposite. Considered together with the validation accuracy, this indicates that the neural network probably did not learn the underlying relationships correctly in this case.

Balancing the optimization of the prediction accuracies and the representativeness of the learned prototypes turned out to be challenging for the given application of hardness prediction. For the approach to become valuable in practice, future work must enable higher prediction accuracies (on validation data), e.g., through an optimized architecture .

9.3 Sintered Gear – Simulation of Sintering

The compaction of water-atomized powder and its subsequent consolidation during the sintering process are decisive for the mechanical properties of a PM component. This is due to the fact that these processes can largely determine the porosity and the shape of the pores. The pore fraction and morphology have a decisive impact on the materials' fatigue strength as well as the surface densification, hardenability, grindability, and performance of the gear. Hence, a multiscale modeling approach is developed to predict the porosity and pore morphology, representing a digital material shadow in the powder compaction and sintering.

The filling of a die with Astaloy 85Mo (FE + 0.85% Mo + C) powder and its compaction can be described by a discrete element approach that aims for the modeling of the interaction between powder particles based on Newton's laws of motion. The particles are defined as agglomerates of spheres that can only undergo elastic deformation. The motion and deformation of each sphere are related to the sum of the forces F_{ij}^{sum} that act between two elements *i* and *j*:

$$F_{ij}^{sum} = F_{ij}^{Con} + F_{ij}^{Coh} + F_{i}^{Grav} \tag{9.1}$$

The contact force F_{ij}^{Con} is calculated by the Hertz-Mindlin model, while the cohesive force F_{ij}^{Coh} represents an additional normal force based on the simplified model of Johnson-Kendall-Roberts. F_{i}^{Grav} includes gravitational forces as well as the contribution of the applied pressure during compaction. Using this approach, the density distribution that is attributed to the friction between the powder and the die as well as between adjacent powder particles can be assessed (Luding 2008).

Static properties, such as the tensile strength, are mainly related to the density distribution, whereas the estimation of the fatigue behavior requires a more detailed assessment of the microstructure. This can be achieved by the application of machine learning. In the field of image generation, generative adversarial networks (GAN) have been applied to a vast variety of problems. A GAN consists of two neural networks, which are referred to as Generator and Discriminator. The former converts an input vector of random values into an image, while the latter is trained to distinguish between generated images and the training dataset. The response of the Discriminator is used to optimize both neural networks. If the training process is evenly balanced, the Generator is empowered to create images that are sufficiently accurate. To account for the influence of relevant variables such as process parameters, an underlying taxonomy is required. Numerical labels are assigned to the images that translate the related process or data conditions, including information such as powder particle size and the magnification of the used microscope. These labels are then embedded in the training process. Linear interpolation techniques, applied to a trained model, enable the prediction of images for new process conditions (Azuri and Weinshall 2020; Goodfellow et al. 2016).

The sintering process is driven by the local gradient of the chemical potential that is directly related to the local curvature. Depending on the temperature, different diffusion mechanisms contribute to the formation of sintering necks and the rounding of pores. Higher sintering temperatures induce a significant contribution of grain boundary and volume diffusion, provoking commonly undesired shrinkage (German 1996). Hence, sintering of conventional PM steel is normally carried out at 1120 °C to mainly activate surface diffusivity, which ensures dimensional stability. Therefore, a mesoscale model primarily requires a physical description of surface diffusion only. The local velocity of the surface of a pore can be described by the surface mobility M and the divergence of the local curvature κ:

$$v = M \cdot \Delta_S \kappa \tag{9.2}$$

The mobility includes the contributions of the surface diffusion coefficient D_S, the surface layer thickness δ, the atomic volume Ω, and the surface energy γ:

$$M = \frac{D_S \delta \gamma \Omega}{kT} \tag{9.3}$$

with T as the temperature and k as the Boltzmann constant.

Instead of modeling the geometry of the powder particles, a level-set-function ϕ is used to continuously describe the interface of the powder and the pore as a signed distance function. The divergence of this function provides the curvature at the surface of the particles. The evolution of the curvature as a function of the time t can be simulated by explicitly solving the advection equation (Bruchon et al. 2012):

$$\frac{\partial \phi}{\partial t} + v \nabla \phi = 0 \tag{9.4}$$

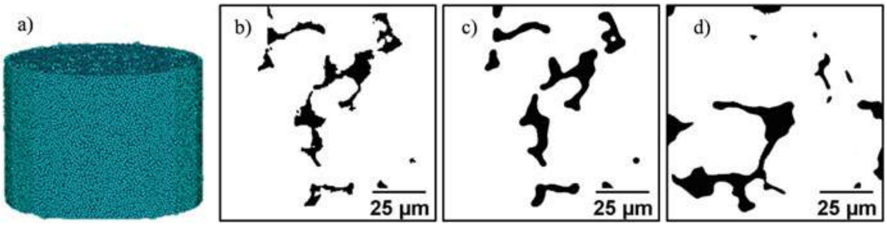


Fig. 9.5 Simulation result of powder die compaction (**a**), predicted microstructure after compaction (**b**), simulated evolution of the microstructure during sintering (**c**), and the corresponding microstructure observed in experiments (**d**)

The methods were merged to predict the microstructure after sintering based on process parameters of compaction and sintering. The GAN was trained for 500 epochs with binary images taken from green samples with variable particle sizes, which were included as image labels. For image recording in the scanning electron microscope, the samples were first embedded and infiltrated with cold resin, then ground and polished following the standard metallographic procedure. After the training, spherical linear interpolation was applied to generate images for a particle size range between 32 and 128 μm.

The feasibility of the proposed method is demonstrated by comparing the results of the model with microstructural images from experiments. Figure 9.5a depicts the simulation results of the compaction process on the macroscale, while Fig. 9.5b shows an image with a size of $100 \times 100\ \mu m^2$ that represents the predicted microstructure with a mean particle size of 83 μm. The subsequent sintering process was assumed to be isothermal at a temperature of 1120 °C with a holding time of 48 min. The simulation result is presented in Fig. 9.5c. The corresponding experimental result, conducted in a quenching dilatometer under vacuum, is displayed in Fig. 9.5d. The predicted pore morphology conveys a good agreement with the experiment.

9.4 Sintered Gear – Surface Hardening and Load-Bearing Capacity

The local surface densification of sintered gears is a promising technique to increase the load bearing capacity drastically. Common methods to densify the functional surfaces of sintered gears are shot peening and cold rolling (Frech et al. 2017). To further increase the material's strength and thus the load-bearing capacity of the gear, a case hardening treatment is conducted after the surface densification. Basically, same processes can be applied to heat-treat sintered parts as in the case of wrought steel parts. However, the effect of the porosity on the material response and the final result of the heat treatment should be considered to choose the optimal treatment strategy and process parameters (Danninger and Dlapka 2018). To study the potential in optimizing the bearing capacity by surface densification and case hardening, an ICME approach is developed, which links simulation blocks that consecutively represent the process steps of carburizing, quenching, tempering and loading of the gear.

Prior to the actual modeling, the density profile in the cross section of the tooth is determined by image analysis of the microstructure and then mapped to the model geometry. The micrographs are transformed into binary images, in which material is represented by white and pores by black pixels. The density of a given area is obtained from the ratio of black and white pixels (Fig. 9.6a). The macro-scale heat treatment model applied in the present work is a finite element modeling approach that comprises the calculation of diffusion, heat transfer, phase transformations, transformation strains, and the elastoplastic material response. Carbon diffusion during carburizing is calculated by the Fick's laws, enabled by defining the temperature-dependent diffusion coefficient and setting corresponding boundary conditions. To model the quenching and tempering stages, a coupled thermomechanical analysis is carried out. The main constitutive law in the mechanical

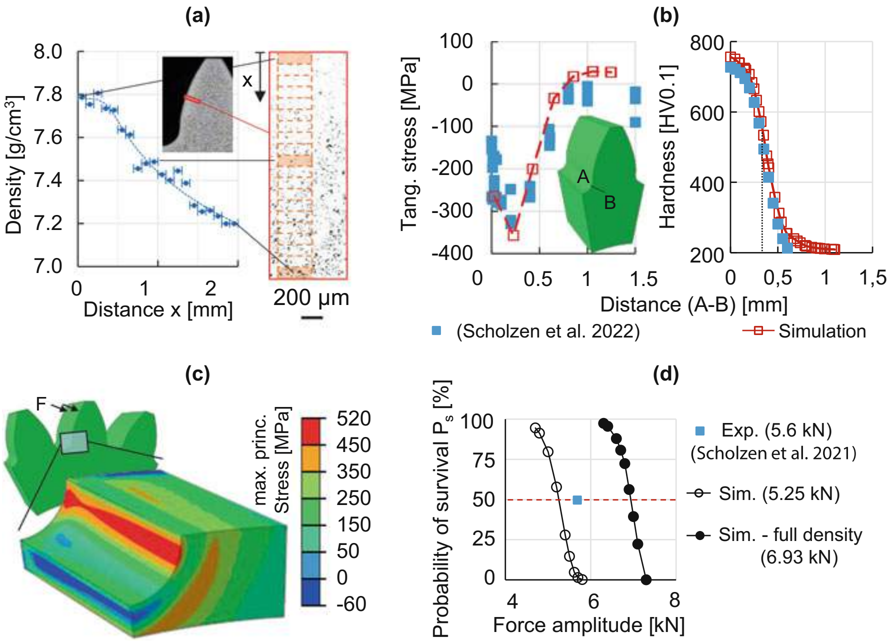


Fig. 9.6 Graphical overview of the modeling approach to predict the load-bearing capacity of a surface-hardened sintered gear, with a module of 3.175 mm and a case hardening depth of 0.3 mm. (**a**) Determination of the density profile, (**b**) simulation of the case hardening, (**c**) simulation of the tooth root bending, and (**d**) calculated load bearing capacity of the tooth root

analysis describes the evolution of the strain tensor and assumes that the total strain rate equals the sum of independent elastic, plastic, thermal, and transformation induced strain rates. The microstructure is described as a continuum, containing calculated volume fractions of different microstructural phases. To describe the overall kinetics of the phase transformations, modified formulations and extensions of the Koistinen-Marburger equation (Koistinen 1959) and the Johnson-Mehl-Avrami-Kolmogorov (JMAK) equation (Avrami 1941) are applied for the martensitic and the diffusion-controlled transformations, respectively. Thermophysical properties of the material are defined depending on the temperature, density, phase fractions, and carbon content. The simulated residual stress state is transferred as the initial stress tensor to the simulation of the loading. Hence, the residual stress is automatically superimposed to the stress tensor resulting from the external loading. More details about the modeling approach are found in Rajaei et al. (2021). Figure 9.6b, c show the simulated hardness and residual stress profiles after case hardening as well as the stress state under loading with a F = 5.25 kN force.

The calculation of the load-bearing capacity is carried out in a post-processing analysis. For each integration point of the FE-model, the local stress and strength values are compared in terms of the local degree of utilization A(x, y, z), i.e., the ratio of the applied equivalent stress amplitude to the fatigue strength under uniaxial loading. The equivalent stress amplitude is determined for a given time-dependent stress tensor according to a proper fatigue criterion, which considers the mean stress effect and multiaxiality. For the example of the tooth root bending, the simple normal stress criterion is still valid, due to the nearly proportional loading case, i.e., constant principal stress directions (Brömsen 2005). The local fatigue strength is calculated for the sintered steel Astaloy Mo85 according to the model suggested in Hajeck et al. (2018), which is developed based on bending fatigue experiments on laboratory samples. The model defines the fatigue strength depending on the density, highly loaded volume, and carbon content, which can be reformulated in terms of hardness. Having the local degree of the utilization, the probability of survival P_s can be obtained as follows:

$$P_s = 2^{-\frac{1}{V_0}\int A(x,y,z)^{k(x,y,z)}dV} = 2^{-\frac{1}{V_0}\sum\left(A_i{}^{k_i}\right)\cdot V_i} \tag{9.5}$$

where V_0 is a reference volume equal to 1 mm^3, k_i is the Weibull module of the integration point i in the FE-model, which accounts for the statistical size effect, and V_i is the volume of the integration point i. The load-bearing capacity is the external force for a survival probability of 50%. Figure 9.6d summarizes the calculation of the tooth root load-bearing capacity. The predicted residual stress and hardness profiles agree very well with experimental results from Scholzen et al. (2022). In Fig. 9.6d the expected bearing capacity of the gear without porosity is given, 6.93 kN. According to the simulation, porosity reduces the bearing tooth root capacity by approximately 25%, compared to a gear with full density.

The prediction of the tooth flank bearing capacity requires a more sophisticated fatigue criterion that is valid for a non-proportional loading and is an ongoing work.

9.5 Sintered Gear – Grinding and Surface Integrity

Grinding is a widely used hard finishing process in gear manufacturing due to high dimension accuracy and improvement of the surface integrity. Currently, the definition of suitable process parameters is performed by elaborate trials or based on the operator's experience. Alternatively, several models for description of grinding loads have been developed for the process of gear grinding in order to regulate the process and to define suitable parameters. However, these models are in general time consuming, which limits their application in production line. In addition, process monitoring for the regulation of the process can also be a challenging task in gear grinding processes due to complex process characteristics. The main objective of this project section is the optimization of the procedure for generating gear grinding with a focus on surface integrity by means of a networked adaptive production concept. In order to achieve this objective, the project is divided into different steps. In the first step, a new process modeling based on the digital twin concept will predict the energy generation according to the material removal rate, given by process parameters and kinematics. In the second step, solutions for real-time measurement methods will be investigated, as well as a connection between real-time measurements and the energy model outputs. Finally, in order to support a wider application of the optimized grinding procedure, a data lake will be built to store relevant data regarding the process under different conditions.

In the following, an explanation of the current status of the first step of the project, regarding the new process modeling is explained. During grinding, a major percentage of the generated energy is converted into heat. Most fraction of this heat is transferred into the gear, and may cause thermal damages. In order to better understand and control the part of the generated heat that flows into the gear, it is first necessary to specify the according energy partition. In the work of Hahn (1966), it was established that the material is removed by each grain of the grinding tool along three different mechanisms: friction, plowing, and shearing. Each of these mechanisms contributes in a singular way to the partition of energy that goes into the gear (Linke et al. 2017). The energy generated in each of the three mechanisms depends on grain-gear micro-interaction characteristics (Malkin and Guo 2007). These micro-interaction characteristics are influenced by the grinding tool topography. The interaction between the grains and the gear is characterized based on both process kinematics and parameters. In order to develop a suitable grinding energy calculation for the generating gear grinding, it is necessary to first consider the single-grain interaction in the contact zone, based on the process parameters.

For the process model developed in this project section, an existing simulation model of the generating gear grinding process based on penetration calculation approach is used. An extension of this simulation model considering a realistic modeling of the topography and the rotational movement of the grinding worm during the process is performed. As a result of the simulation, micro-interaction characteristics for each of the engaging grains are obtained and used for the calculation of the energy in generating gear grinding.

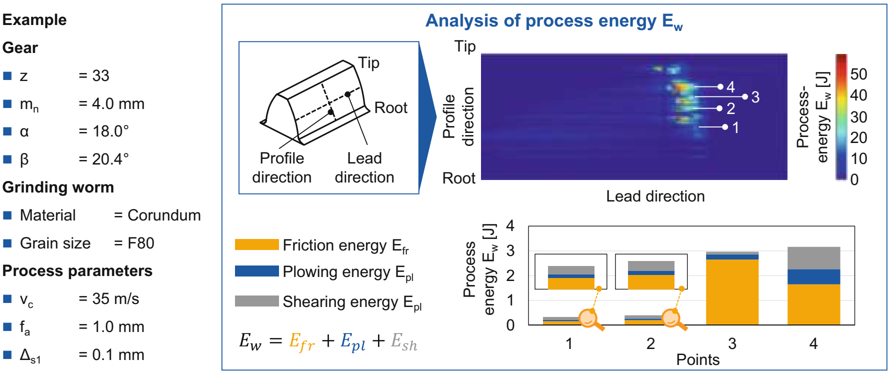


Fig. 9.7 Analysis of the energy calculation for generating gear grinding process

The results of the process energy E_W calculated with the extended simulation model are shown in the upper right of Fig. 9.7. The gear, grinding worm, and process parameters used for the calculation are shown in the left side of Fig. 9.7. For better visualization, the calculated process energy E_W was plotted onto the flank of the gear. In the visualization, the process energy E_W corresponds to the energy generated by grinding in one specific axial position. Therefore, only one area of the gear flank was ground in the simulation, and not the entire flank.

In the four points highlighted in Fig. 9.7, a further analysis of the energy was performed, which is shown in the diagram in the lower right side of Fig. 9.7. For the points one and two, similar process energies and contributions are obtained. In the points three and four, the process energies E_W are also similar to each other, but the contributions of each individual energy of each chip formation mechanism are different. The importance of an analysis of the process energy E_W considering the chip formation mechanisms is due to the fact that each of these mechanisms has a different partition of energy that goes into the gear. According to Malkin (Linke et al. 2017), almost all the friction energy E_{fr} is conducted as heat to the gear, while for plowing E_{pl} and shearing E_{sh} energies, this fraction is smaller. The fraction of energy conducted as heat to the gear for the shearing mechanism is the lowest of the three mechanisms (Linke et al. 2017). Therefore, if a significant part of the process energy E_W corresponds to shearing energy E_{sh}, most of this energy is used for chip removal and not to heat to the gear. If most of the process energy is not converted to heat, the possibility of grinding burn during the process decreases. Due to this, even though the points three and four presented similar process energies E_W, the contribution of each individual energy of each chip formation mechanism is different for each of these points, leading to different amounts of heat transferred into the gear. Based on these results, the method for the calculation of the process energy E_W for generating gear grinding was able to show sensible outcome. Ultimately, this method can be used in the future for the prediction of grinding burn for the generating gear grinding. For this, the critical values of the individual energy of each chip formation mechanism and their influence on the grinding burn presence need to be defined.

9.6 Drive Shaft – Open-Die Forging

Open-die forging is a bulk metal forming process that can be used to produce mostly longitudinally oriented components such as drive shafts or axles with excellent material properties. In open-die forging, the ingot is incrementally formed into the desired shape using two simple dies that perform so-called strokes. Forging processes are summarized in pass schedules that contain the important process parameters like height reductions or press velocities for each individual pass. A forging pass consists of a discrete number of consecutive strokes that are oriented in the same ingot direction and hence, deform a defined region of the ingot.

Since commonly hundreds of individual strokes can be involved in an open-die forging process, there are a large number of process routes that lead to the same final geometry. However, these different processes are not equivalent from a production point of view, as they have different process times, energy consumption and, most importantly, can produce different material properties in the final part. Therefore, both the targeted process design and the detailed monitoring and tracking (digital shadow) of individual open-die forging processes as well as their corresponding down- and upstream processes are very useful for the reliable and efficient production of forgings with excellent material properties.

Since important material and workpiece properties often cannot be measured directly during the open-die forging process, an assistance system for open-die forging was developed that is able to monitor the current state of the forging ingot live, throughout the process (Rudolph et al. 2021). Besides information on temperature and geometry, the equivalent strain introduced along the core fiber is determined using a fast calculation model. Afterward, the combined time-dependent information on temperature and equivalent strain enables the calculation of the grain size present insight of the ingot during and after forging, using a fast material model based on JMAK-equations (Karhausen and Kopp 1992) (ICME) and hence, laying the foundation for a digital shadow of the forged component. The process data insight of the digital shadow can be used to subsequently set up an FE-model and hence, to enrich, e.g., locally restricted information from the fast process models. Here, for example, three-dimensionally resolved temperature and equivalent strain trajectories can be generated and incorporated back into the fast microstructure model to calculate a three-dimensional distribution of the grain size in the component over the course of the forging.

Although the process route has a decisive influence on the component quality, the process design in open-die forging is still often based on experience or simple models, resulting in a need for new approaches on the targeted process design. Since compared to, e.g., die casting, which is used for producing high-volume batches, the batch sizes in open-die forging are rather small. Hence, data from real forgings is not widely available, limiting the usability of modern data-driven algorithms that require large amounts of data for their application. Therefore, a case-based reasoning (CBR) (Richter and Weber 2016) agent for the targeted design of pass schedules for the open-die forging process is developed. Similar to the human experience-based behavior, CBR is a methodology to learn based on experience by remembering past problems (cases) and the way they were solved (solutions). By recording data of past forging processes (digital shadows) and complementing those with data of simulations and fast process models, the CBR-agent shall make suitable recommendations for a new case that requires a pass schedule. However, it is not sufficient to consider individual steps in a production chain of products. Decisions to be made range from the material selection, heat treatment specifications, press and tool allocation, and pass schedule layout to the final machining steps. Typically, the required knowledge to make informed decisions is spread across different stakeholders (cf. Fig. 9.8). For example, the material choice for a drive shaft, considering a set of requirements, may depend not only on the prices and availability of the different steel alloys at the retailer ("steel retailer"), but also on the available material characteristics required to simulate and design the forging process ("IBF-agent") as well as the heat treatment strategy ("IWM-agent") or the machining process ("WZL-agent").

While the internet is heavily used in the everyday lives to accumulate information, there is typically no unified network between different industrial stakeholder, which could be used for planning complex manufacturing processes. A decentralized World-Wide-Lab (WWL) infrastructure, where companies and research labs can offer their services, is required in order to solve such complex tasks efficiently, supported by autonomous agents. A service agent may range from simple data vendors, e.g., a retailer (cf. Fig. 9.8, "steel retailer") informing about prices and availability, to complex process control nodes that automatically interact with other's agents in the WWL, in order to accumulate data to plan out the manufacturing process for a whole product. The WWL ensures semantic interoperability between the different agents through the use of ontologies. Interfaces are specified using the Thing Description ontology (Kaebisch et al. 2020) and agents need to agree on a core ontology that structures the information about production processes. Individual agents may extend this core ontology, if needed.

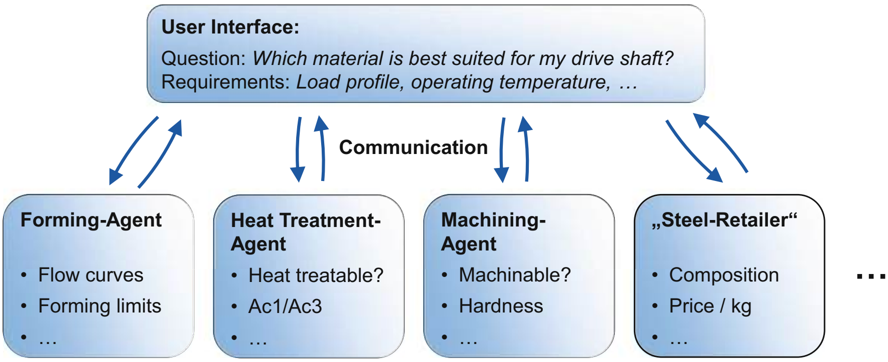


Fig. 9.8 Schematic representation of communicating WWL-agents of different process steps for solving an exemplary production-related problem

Data provenance information plays an integral role in the vison of a WWL, hence several requirements specified in the FactDAG model (Gleim et al. 2020) for data provenance information are covered by WWL agents. Agents need to be able to find other participants of the WWL, so that they are aware of possible collaboration opportunities. To keep the structure decentralized, each agent maintains a local service cache that can be expanded by scanning the network via User Datagram Protocol (UDP) multicasts.

Combining the digital shadow, e.g., of each forged drive shaft with the new possibilities of the WWL it shall be possible to adapt subsequent manufacturing steps such as heat treatment or mechanical processing based on the previous individual manufacturing process. Moreover, assumed the digital shadow of a forged drive shaft is complemented by component-specific information on the downstream production processes, an individual long-term estimate of, e.g., the service life of the component (ISHE) might be possible in the long run.

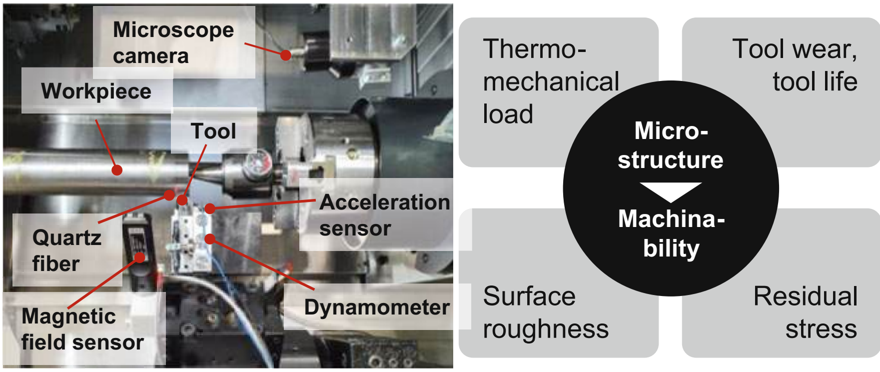
9.7 Drive Shaft – Machinability

The machinability of a material is one of the most important input parameters for an optimized process design. It determines, apart from the tool wear and the achievable chip removal rates, the surface integrity as well as the functionality of the finished component. The machinability of a material is dependent on the microstructure, controlled by the chemical composition and the heat treatment state, and thus offers a very wide field in the area of basic research and industrial application (Abouridouane et al. 2019).

In order to determine the influence of the microstructure on the machinability of drive shaft, a new experimental setup with automatic multi-sensor data acquisition has been developed for in-process measurement of thermo-mechanical load and tool wear during turning operations (see Fig. 9.9). In order to check the performance of the proposed experimental setup and to derive correlations between the operating thermo-mechanical load and the machined surface characteristics, longitudinal finish turning tests on drive shafts made of steel 42CrMo4 with two different microstructures are carried out using carbide indexable inserts.

A summary of the main results obtained in the present research work can be given as follows:

- The proposed experimental setup is suitable for in-process measurement and analysis of the thermo-mechanical load and tool wear by turning operations.
- The thermo-mechanical load, which depends to a large extent on the hardness of work material, controls the tool wear and the resulting surface finish as well as the induced residual stresses.
- The measured roughness R_Z shows obviously the bad influence of the tool wear on the achieved surface quality when finish turning drive shaft.
- The achieved surface integrity results can be incorporated in digital twins for process monitoring to optimize cutting process performance.



Target quantity (mean values)	Shaft 1	Shaft 2
Hardness / HRC	26	24.8
Cutting force / N	120	110
Surface temperature / °C	85	70
Tool flank wear VB / µm	115	98
Surface roughness R_z / µm	6.6	4.6
Residual stress / MPa	390	210

Workmaterial:	42CrMo4	Cutting speed:	150 m/min
Tool:	CNMG 120408-PM 4315	Feed:	0.15 mm
Cooling:	Dry cut	Depth of cut:	0.5 mm

Fig. 9.9 Multi-sensor experimental setup for machinability characterization

A multiscale approach was developed to predict the mechanical yielding behavior of the work material and thus its machinability. The modeling of the constitutive behavior of the considered materials poses several challenges at different levels. All following assumptions and models follow closely the choices of Laschet et al. (2022).

First, the elastic and plastic behavior of pearlite and ferrite must be modeled. For ferrite, a cubic elastic behavior is considered and its plastic behavior is assumed to be governed by a dislocation-based approach, which then determines the corresponding yield stress. Here, the dislocation density ρ is assumed to be governed in terms of the plastic strain ϵ_p by the following approach (modified Kocks-Mecking-Estring model) (see Laschet et al. 2022 for details).

$$\frac{d\rho}{d\epsilon_p} = M\left(\frac{k_1}{b}\left(1 - \exp\left(-\psi\sqrt{\rho}\right)\right) - k_2\rho + \frac{k_3}{b\,D}\exp\left(-\frac{M\lambda^*}{b}\epsilon_p\right)\right) \tag{9.6}$$

The evolution of the dislocation density of ferrite is influenced by the parameters $p_F = (\psi, k_1, k_2)$, while all other quantities are kept constant. For cementite, its elastic behavior is assumed as orthotropic. The evolution of the dislocation density of cementite is assumed to be governed by the following approach (hardening law of Gutierrez-Altuna type):

$$\rho = \frac{1 - \exp\left(-k_2 M \epsilon_p\right)}{b k_2 L} + \rho_0 \exp\left(-k_2 M \epsilon_p\right) \tag{9.7}$$

The dislocation density of cementite and its corresponding yield behavior are assumed constant (see Laschet et al. 2022 for details).

Then, a representative volume element (RVE) is generated at the “nano” and “micro” levels. At the nano level, a bilamellar RVE representing the ferrite-cementite-structure of pearlite is generated with ABAQUS. The nano RVE considers the statistics measured in experiments, i.e., the volume fractions of ferrite and cementite and the lamellar lengths. At the micro level, a polycrystalline RVE is generated with DREAM3D, considering the microstructure statistics, e.g., average grain size, volume fractions of ferrite and pearlite.

The final yield stress curve (computed then with the nano/micro RVEs and the software HOMAT) depends then on the specific choice of the parameters for ferrite. It is further assumed that the plastic behavior of ferrite in pearlite at the nano level and in the polycrystalline arrangement at the micro level differ, such that corresponding parameters $p_{F,nano}$ and $p_{F,micro}$ (in total six parameters) are optimized separately. An optimization loop is setup in Python with the LIPO package for derivate and parameter-free global optimization built upon the C++ dlib package. In this loop, for every new set of values for the optimization variables $p_{F,nano}$ and $p_{F,micro}$, the effective elastoplastic behavior of the nano RVE is computed and passed on as the pearlite phase to the micro RVE. Then, the effective plastic behavior of the micro RVE is computed and the resulting yield behavior is compared to experimental data. The loop continues improving the parameters until a maximum number of iterations is reached. The final optimized yielding behavior at the micro level can then be passed on for macroscopic simulations.

9.8 Summary

This chapter illustrated several approaches to model materials’ response along a wide range of manufacturing processes. In general, the common objective is a predictive and quantitative description of the process-microstructure-property interactions on different time and length scales. However, the concrete questions, target values, boundary conditions, and approaches must be defined specifically for the considered application. The presented ICME-approaches provide valuable predictions of the microstructure and accordingly the component properties by means of sophisticated physical and empirical models, i.e., digital twins, as in the simulations of the sintering, heat treatment, and grinding. Data-driven and fast approaches, i.e., digital shadows, as in fine blanking, open-die forging and machining can be integrated into the process control and act as in-situ digital sensors that provide essential information about hard to acquire parameters. Finally, knowledge-based approaches, e.g., case-based reasoning, can link different sectors of expertise together and provide the infrastructure to integrate the material-experts' knowledge along the entire development, production, and operation cycles.

The vision of the future work is to provide robust digital tool boxes to be integrated already in the early phases of the planning and designing toward an agile product development and production. To facilitate the use of the future tool box, standard data formats should be defined for all input and output data of the models. Furthermore, codes and models should be parametrized and proper simulation platforms, e.g., AixVipMap, should be adopted to automatically run multi-step simulations and produce large data. With the help of capable database and ontology solutions, the simulation data and the knowledge gained would be collected to form a data lake. On this basis, AI methods become applicable to deepen the understanding of complex physical interactions between process, material, and components performance and give suggestions for holistic optimization of the production.

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Part IV

Production

Internet of Production: Challenges, Potentials, and Benefits for Production Processes due to Novel Methods in Digitalization

10

Christian Hopmann, Gerhard Hirt, Mauritius Schmitz, and David Bailly

Contents

Abstract

In industrial production, customers' requirements are rising regarding various aspects. Products have to be produced more economical, more flexible, faster, and with much higher quality requirements. Furthermore, especially for traditional mass production processes, shorter product cycles increase the demand in rapid production and process development. The inherent increased product and production complexity raises additional challenges not only in development but also in setup and operation. Lastly, upcoming requirements for sustainable production have to be incorporated. These conflicting aspects lead to increasing complexity for production development as well as production setup at each individual production step as well as along the complete value chain. To master these challenges, digitalization and data-driven models are fundamental tools, since these allow for the automation of many basic tasks as well as processing

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of large data sets to achieve process understanding and derive appropriate measures. This chapter illustrates requirements for digital systems to be created and benefits derived by different novel systems. Furthermore, because modern systems have to incorporate not only single processes but complex process chains, various production processes and assembly processes are taken into account. In the following chaps. 13, "Decision Support for the Optimization of Continuous Processes Using Digital Shadows," 14, "Modular Control and Services to Operate Lineless Mobile Assembly Systems," 12, "Improving Manufacturing Efficiency for Discontinuous Processes by Methodological Cross-Domain Knowledge Transfer," and 11, "Model-Based Controlling Approaches for Manufacturing Processes," digitalization and Industry 4.0 approaches are presented, which incorporate data-driven models for a wide variety of production processes and for different time scales. Many techniques are illustrated to generate benefits on various levels due to the use of data-driven, model-based systems, which are incorporated into a digital infrastructure.

Keywords

Digital shadows · Digitalization · Smart manufacturing · Complex value chain · Automated production

10.1 Introduction

Production technology has come a long way since the early beginning of industrial manufacturing. Starting with the First Industrial Revolution, which incorporated machine based production using steam-powered or water-powered machines, industrial manufacturing has steadily improved regarding efficiency and speed. In the Second Industrial Revolution, logistic infrastructures and electricity like railroad tracks and assembly belt production lines have boosted industrial production and extended it toward a broader field of view. The Third Industrial Revolution, introducing electronic systems, microcontroller, and embedded systems, further increased the efficiency and set the foundation for the Fourth Industrial Revolution, which is still ongoing as about 64% of the companies are still at the beginning of the digital transformation (Xu et al. 2018; PwC 2022). This Fourth Industrial Revolution aims at establishing a flexible production, which is capable of adapting production toward changing requirements regarding product complexity, quality, and speed while increasing customer satisfaction via production on demand or individualized products. Furthermore, it aims for optimized processing regarding quality and costs as well as sustainability (Ghobakhloo 2020). To achieve this, the use of data along the value chain is the main enabler (PwC 2022).

In general, this development is driven by certain factors like increasing complexity (information intensity), increasing demand for customizability and functionality, flexibility, efficiency benefits through standardization and the substitution of competencies, resilience, as well as the improved information exchange with partners and customers. This is underlined by more than 1 Bio. € investments into digital manufacturing sites yearly, which makes an annual investment of 1.8% of the net revenue (Andal-Ancion et al. 2003; Christensen 2016; PwC 2022).

In the following, we discuss which challenges arise for production technology due to consumer and customer requirements and which challenges have to be met to achieve a production according to Industry 4.0. Furthermore, we discuss, how these can be overcome by novel approaches in the field of production processes and assembly processes, leading to actual benefit for production.

10.2 Challenges for Industrial Manufacturing

In industrial production, customers' requirements are rising regarding various aspects. Products have to be produced more economical, more flexible, with more variants, faster, and with much higher-quality requirements. Furthermore, especially for traditional mass production processes, shorter product cycles increase the demand in rapid production and process development as well as faster product changes in production.

These diverse requirements result in higher complexity regarding all areas of production including product design, process development and planning, as well as mastering the production processes itself. Furthermore, each area including all needed assets has to be coordinated and fine-tuned to the current change requirements. To be able to achieve this, the right data at the right point in the process chain has to be acquired in the first place. Due to the complexity involved in production, this can be an extensive task, since, many domains are included in these processes ranging from sales and order management, process development, process planning to manufacturing. Additionally, each domain involves a large variety of interfaces, protocols, and formats as well as different semantic information (Fig. 10.1).

Especially on the production shop floor, data interfaces of machinery vary depending on the individual configuration and the age of production machines. Therefore, connectivity ranges from no usable data interface to file-based storage or export to locally accessible interfaces like RS232/485 or bus-driven systems to modern Ethernet-based interfaces like OPCUA. Additionally, data introduced by the human via human-machine interfaces (HMI) has to be considered. Depending on the task, for which the data is intended to be used, requirements are created regarding acquisition speed as well. For real-time applications, for example, not all data acquisition methods are capable of providing data at the necessary sampling rates. If a direct feedback has to be given to achieve a defined task, the used interface has to be capable of accepting input data and perform actions accordingly, which is again not provided by any interface (Rostan 2014; Hopmann and Schmitz 2021; Cañas et al. 2021; OPC Foundation 2022).

Lastly, interfaces also do not specify the semantic information, which is provided, such that domain knowledge and experience is necessary to define which information has to be used and how it will be used. This leads to lots of manual overhead

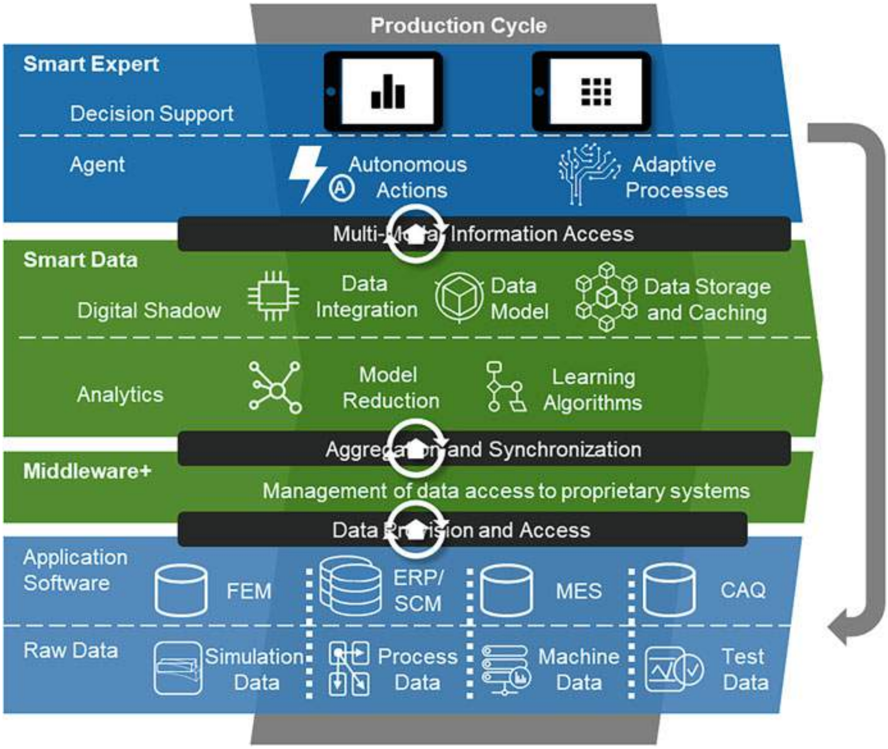

Fig. 10.1 Schematic flow of data for a digital shadow of a single production process

by individual configuration and establishment of data pipelines, which makes data engineering a non-negligible expense. Additionally, interdisciplinary skillsets are necessary to be able to perform these integration tasks.

If the capability of data acquisition is established, the data has to be processed, stored, and/or provided to other systems. Data processing itself can be performed in many different ways using varying hardware and software. The appropriate technology again has to be chosen based on the requirements of the task, which has to be performed. Rapid development in Internet of Things (IoT) technologies on the one hand provide a variety of tools; on the other hand, the landscape of tools and technologies for data integration and digitalization got complex and diverse (Cañas et al. 2021).

For real-time applications, for example, data has often processed in close proximity to the process, since the latency introduced by the network due to protocol overhead or wire length cannot be accepted. For such applications, edge devices are used, which reduce latency and locate the processing power close to the data source. For other applications like inline optimizations, higher latencies are acceptable, and processing can therefore be performed on a more economical server infrastructure (Pennekamp et al. 2019; Cao et al. 2020; Hopmann and Schmitz 2021; N.N. 2022).

Processing also relies on algorithms and models analyzing the data and deriving appropriate outcomes. Depending on the complexity and computational effort, the software and hardware have to be chosen to meet these requirements regarding execution times.

Finally, the data has to be stored and/or provided to other systems. Therefore, the right concepts for databases, data warehouses, or data lakes have to be considered, which fulfill requirements regarding storage capacity and database interaction speed (Nambiar and Mundra 2022).

To actually generate benefits for production, the data has to be appropriately processed. This includes an aggregation of all necessary data, which itself often relies on specific domain knowledge to establish an acquisition of the right data sources and process-specific settings or parameters. These sources can be machine interfaces, sensors, human-machine interfaces, dedicated databases, or further sources. The data has also to be aggregated and interpreted to be used as digital representation (digital shadow) of a specific use case. Furthermore, task-specific models have to be created based on this data to represent the targeted use case and identify appropriate measures. In process technology, the range of modeling techniques is huge, ranging from physical motivated models to data-driven models, and the most suitable one has to be identified to achieve the highest benefit (Cañas et al. 2021).

Another requirement is an increasingly flexible production, which is capable of changing manufactured products more rapidly while reducing overhead for each product change. This can on the one hand be achieved due to data availability and suitable models to optimize the available machinery. On the other hand, the processes and machines have to be developed toward these requirements to overcome the limitations of the physical capabilities. Therefore, improvement of the production processes or novel manufacturing approaches have to be developed.

10.3 Potential and Benefits

Production processes get increasingly difficult to handle and operate at the optimal processing conditions due to the complexity in process control and machine operation as well as influencing factors like varying material properties and ambient condition. Furthermore, for overall process efficiency, not only a single process has to be observed but also previous and following processing steps. In addition to the complexity of the individual process itself, demanding a high skillset to be developed and operated, the processes interact with other such processes as well as with the processed material and the environmental conditions.

One important potential of digitalization for production is to achieve an improved transparency of production processes, enabling various benefits on the management and operation level. From the management point of view, transparency assists the operators to supervise more production processes simultaneously and be able to rapidly react to changing states like drifts in process quality or unforeseen production changes. This can be achieved with a wide variety of techniques, starting with raw data illustration, extended by computation of KPIs to increase information density to complex techniques like soft sensors, incorporation of simulation data, or improved quality measurements. In the following chapters, use cases for these methods are illustrated at the processes of milling, extrusion, and condition monitoring of ball screws.

The gained transparency also enables operators to get a more sophisticated insight into the process itself, and these are assisted to understand the behavior of a process more deeply. Therefore, the operator is able to set up and operate the process more efficiently and generate improved manufacturing speed or product quality. Data about the state and condition of the process has to be processed and made available to the operator in a condensed and understandable manner.

If this potential is reached, further methods for automatic decision development can provide the operator with guidance in the form of an assistance system. In this case, the operator does not necessarily have to understand the process in detail, but is guided by a model-driven system. A model-driven system analyzes the process and develops a suitable measure. To be able to do so, novel systems are developed based on physical and data-driven models in combination with machine learning approaches, which are capable of modeling complex production processes and lead to higher process efficiency or higher quality. In the following chapters, such methods are illustrated for the use cases of welding, laser drilling and cutting, injection molding, fine blanking, or coating.

Furthermore, systems are developed, which automatically plan or interact with the process to achieve the highest efficiency or speed. The use case of assembly illustrates how a combination of novel information infrastructure coupled with standardized formats and model-driven decision-making systems enables an efficient, fast, and flexible assembly process while incorporating various boundary conditions.

The overall benefits can be stated as follows:

- Higher transparency in production
- Increased information availability
- Improved process understanding
- Higher process efficiency
- Higher process and product quality
- Increased flexibility
- More resilient processes

10.4 The Approach of the "Internet of Production"

As illustrated in Fig. 10.2, within the "Internet of Production," a holistic approach is pursued to enable production technologies for upcoming requirements.

At the process level, many different process technologies are investigated to be able to address different process requirements and applications. These can be structured in applications requiring real-time or fast data acquisition and processing in combination with reduced models to achieve real-time computation,

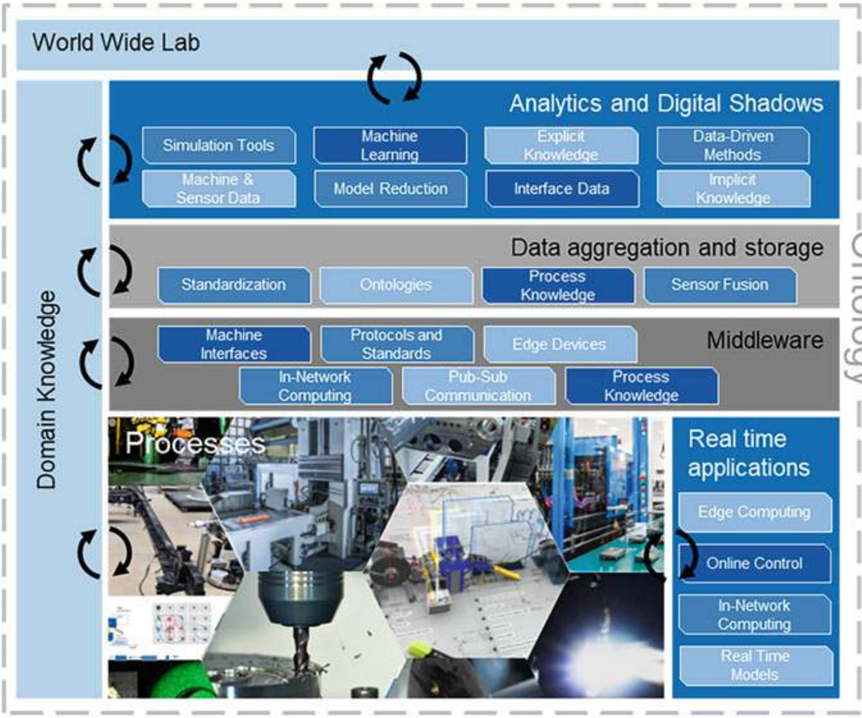

Fig. 10.2 Holistic approach for production technology

discontinuous and continuous processes to cover the development for online and inline digitalization methods, as well as ontologies and semantics for both types of processes and assembly processes, which inherit a close connection to prior processing step and introduce many boundary conditions and a great variety of submodels to be accessed.

For each process technology, data acquisition is performed with industry domain-specific interfaces and formats as well as additional sensors. For this area of data engineering, knowledge with respect to industrial data interfaces as well as intense domain knowledge about the process and the necessary data sources is required. To efficiently master data engineering and data processing, an extremely interdisciplinary and wide skillset is necessary (Pinzone et al. 2017). Some domains, which are considered in the following chapters, are milling, rolling, extrusion, injection molding, high-pressure die casting, open die forging, fine blanking, welding, coating, laser cutting, and industrial assembly using various approaches.

Furthermore, different information infrastructure concepts are used. For time-critical processing, edge computing is used to enable fast signal processing for closed-loop milling control to achieve higher process and part quality (Schwenzer 2022). For complex tasks with many data sources, sub pub infrastructures are used to organize information, make information available, and provide it to a cloud-based modular infrastructure (Buckhorst et al. 2021). Furthermore, database-oriented approaches are investigated like continuous data storage for continuous processes like rolling or extrusion.

As stated earlier, data processing is performed according to the specific task and specific domain using suitable models. For production technology, one important branch of models is created using analytical approaches like physically motivated models or models based on finite element simulations (Hopmann et al. 2019).

To bridge the gap between individual and domain-specific knowledge, a common definition of semantic dependencies is developed based on the Web Ontology Language OWL. Ontologies were developed for a standardized and formalized description of knowledge and can therefore be used to formalize knowledge and especially relationships between all occurring assets in production, may it be the used material, the manufacturing process, the order along the value chain, or the actual product. OWL therefore uses standardized formats in XML, RDF, or RDF-S format (World Wide Web Consortium (W3C) 2003). Using a standardized syntax and a standardized definition allows applications to electronically interpret the information and automate currently manually performed tasks like data aggregation or data interpretation. Furthermore, a common standard for data interchange in terms of formats for data exchange is developed. Along with the research in the field of “Infrastructure” of the “IoP,” which focuses on Asset Administration Shells (ASS), a methodology to automatically connect data sources using a given ontology and available ASS is developed. Asset Administration Shells define a standardized way for defining and also establishing connectivity to an Industry 4.0 asset. It can be used either as a passive ASS, providing necessary information for an asset, or actively as a standardized communication interface with the interface (Tantik and Anderl 2017; Sapel et al. 2022).

Furthermore, data exchange has also to be shared outside of trusted boundaries like the shop floor or company boundaries. Therefore, suitable data exchange interfaces have to be used in combination with suitable security measures, to provide information only to authorized systems in a necessary granularity. Additionally, approaches have to be developed, which preserve the intellectual property of the instance providing data. This can, for example, be achieved using anonymization techniques or dedicated systems, which process the given information and only provide the results or calculated measures (Pennekamp et al. 2019, 2020).

By this global connectivity, benefits can be derived throughout whole value chains, and the increasingly valuable good data can be most efficiently used, creating a World Wide Lab.

10.5 Conclusion

The increasing requirements on production processes, resulting from increasing demands of customers and consumers, result in the need of increasingly complex processes and the need for using the maximum potential of each processing process. Both aspects result in the need of handling rapidly changing, multidimensional, and complex problems. To master these problems, adaptive smart systems are necessary, which process all given information and derive optimized measures. Especially data-driven and model-based systems are capable of achieving this, especially in the field of processing technology, since these are capable of working on small sample sizes. Furthermore, such smart systems have to be deployed in an economic manner to avoid cost overhead when introducing new products or changing production. Modern information technology along with standardization has the potential for automating and fastening digitalization of existing and new production assets. Domain knowledge along with data-driven modeling furthermore enables the creation of digital representations of the processes (digital shadows) to evaluate and optimize those. Nevertheless, one of the greatest challenges is to master the high degree of interdisciplinarity necessary and bring together all needed skillsets for a successful implementation.

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Model-Based Controlling Approaches for Manufacturing Processes

11

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Abstract

The main objectives in production technology are quality assurance, cost reduction, and guaranteed process safety and stability. Digital shadows enable a more comprehensive understanding and monitoring of processes on shop floor level. Thus, process information becomes available between decision levels, and the aforementioned criteria regarding quality, cost, or safety can be included in control decisions for production processes. The contextual data for digital shadows typically arises from heterogeneous sources. At shop floor level, the proximity to the process requires usage of available data as well as domain knowledge. Data sources need to be selected, synchronized, and processed. Especially high-frequency data requires algorithms for intelligent distribution and efficient filtering of the main information using real-time devices and in-network computing. Real-time data is enriched by simulations, metadata from product planning, and information across the whole process chain. Well-established analytical and empirical models serve as the base for new hybrid, gray box approaches. These models are then applied to optimize production process control by maximizing the productivity under given quality and safety constraints. To store and reuse the developed models, ontologies are developed and a data lake infrastructure is utilized and constantly enlarged laying the basis for a World Wide Lab (WWL). Finally, closing the control loop requires efficient quality assessment, immediately after the process and directly on the machine. This chapter addresses works in a connected job shop to acquire data, identify and optimize models, and automate systems and their deployment in the Internet of Production (IoP).

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11.1 Introduction

This chapter focuses on low-level machine and sensor data from manufacturing processes. Data within the Internet of Production (IoP) can be sourced at different layers, ranging from a single sensor over a production cell to the shop floor and, finally, to the World Wide Lab (WWL) where information is exchanged globally across company borders (Pennekamp et al., 2019).

Figure 11.1 visualizes the different process layers of production technology according to three process durations (left), which range from milliseconds to days. The involved parties (exemplary) and their influence (right hand side) further differ with each process layer.

The workpiece as the core layer is influenced by events occurring within milliseconds, while the assembly is handled in the context of further production steps and ranges in minutes. The final product may ultimately involve the supply chain, which may range over days. Therefore, each process layer requires specific methods of data acquisition and processing to be able to control their specific quality requirements. The connection of the different layers is a major challenge within the IoP.

In this chapter, we initially focus on low-level data sources on the shop floor. Here, raw data from production processes is recorded by sensors directly at the production devices. Thus, any resulting manipulations can have an immediate impact on the process. More specifically, the proximity to the production processes requires a tight connection of data-driven methods and expert knowledge of the

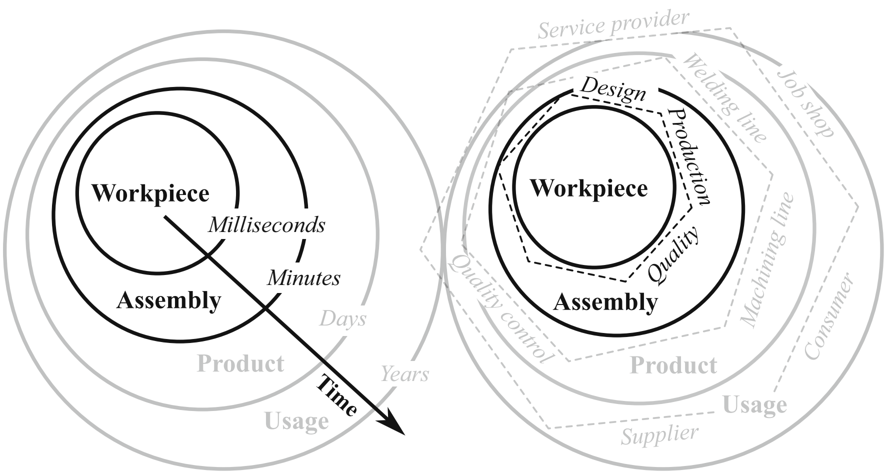

Fig. 11.1 The process layers of production technology involve different time scales, ranging from close control loops to information flows during usage, and various parties (black: subject of this chapter, gray: upcoming research) (Mann et al., 2020). (With kind permission of Springer Singapore)

production technologies to advance the state of production. By using combinations of technological information and data-driven methods in so-called gray box models, it is possible to utilize raw data to control the processes directly and provide useful information for high-level domains, such as process planning (cf. [Resilient Future Assembly Systems Operation in the Context of the Internet of Production]), production management (cf. Part V, "Production Management"), or production development (cf. Part VI, "Agile Development"). A digital shadow (Brauner et al., 2022) holds the resulting information and models and is the foundation for different approaches, thus enabling a better understanding of processes on shop floor level (cf. Jarke et al. 2018). In line with the vision of the IoP with its WWL, models are expected to be transferable to and (re)usable by other stakeholders and production sites with their own machines, shop floors, and domain experts. Thus, the continual and iterative exchange of process information allows for even more advances. We summarize this vision and our methodological approach in Fig. 11.2 following an abstract closed-loop control scheme.

The system that is to be controlled is represented by the machine and the process on the shop floor (upper right, green area). Information is gathered by different sources, combined via sensor fusion, and pre-processed before it is contextualized using expert knowledge (lower center-right, blue area). The enriched data is used to identify, build, and optimize gray box models (center, yellow area), which themselves are used for decision support and autonomous control systems of the machine and processes (upper center, red area). Models and data are shared within the IoP to connect different shop floors (left, gray area). To enable this complex exchange of information, common ontologies across company and even technological borders are necessary and need to be established. Existing ontologies (e.g., process specification language (PSL) (Grüninger, 2004)) do not suffice the necessary requirements in terms of cooperation within the IOP. This especially holds for low-level models and data, which have strong adaption to specific manufacturing technologies.

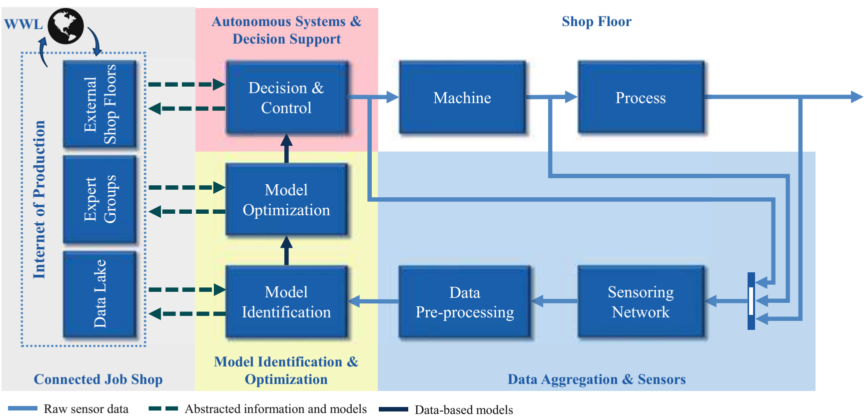

Fig. 11.2 Abstract scheme of a model-based control system for manufacturing processes

This chapter addresses different aspects within the scope of connected and controlled processes following the structure in Fig. 11.2 and is organized as follows: First, Sect. 11.2 provides a general state of the art covering methodical fundamentals. Subsequently, Sect. 11.3 covers approaches and methods in the subsystems' data aggregation and sensors (Sect. 11.3.1), model identification and optimization (Sect. 11.3.2), autonomous systems and decision support (Sect. 11.3.3), and the model usage in connected job shops (Sect. 11.3.4). As technological aspects remain essential, the developed methods are demonstrated on several domain-specific use cases in the manufacturing fields of milling and welding. A conclusion of the chapter and discussion of future challenges is in Sect. 11.4.

11.2 State of the Art

The overarching scheme (cf. Fig. 11.2) of the applied approaches spans a wide field of disciplines. Applying the idea of the IoP on these disciplines requires specific fundamentals, which can roughly be grouped into three topics: data acquisition and semantics, model optimization, and model-based control and decision. Data acquisition and data semantics or ontologies both concern the flow of data from its source to the model identification and optimization at the center of Fig. 11.2. While the former describes dependencies and provides transferable knowledge from previous processes within the WWL, the latter helps optimizing and tailoring to the specific processes by contextualizing this transferable knowledge, e.g., using existing domain knowledge or hybrid, gray box modeling approaches. Finally, the optimized models are utilized in advanced control approaches to maximize the productivity while accounting for constraints regarding quality and safety. Eventually, the tailored models are fed back into the collective database. In the following, a brief overview of the fundamentals regarding these topics is given to enable further understanding of the applied approaches and their interconnection.

Data acquisition in connected job shops Acquisition of data across the shop floor remains an obstacle along industrial production systems. The high costs of sensors, acquisition systems, and infrastructure as well as the costs for connection and configuration of multiple assets discourage investments. The machines themselves, however, come with a significant amount of data sources. Such data was initially only used for control purposes, e.g., positioning the machine axes as precisely and as fast as possible. However, to monitor the machine tool, or even establish a digital shadow of the manufacturing process, it is essential to systematically collect and store said data (Siemens, 2022).

Internal machine data as well as further data from external sources can be combined in a digital shadow of the process using data fusion techniques. Data fusion is the combination of different sensors to a single information, enhancing signal quality and reducing uncertainty. According to Hall and Llinas (1997), data fusion can be done on three different levels: (i) raw data level, (ii) feature or state vector level, and (iii) decision level. The main challenge when fusing these different signals is maintaining the high-quality information within the signal without deteriorating the information by overly relying on poor signals (Hall and Llinas, 1997).

Model-based controllers Model Predictive Control (MPC) is an intuitive control algorithm which explicitly considers process knowledge (by an according model) to optimize the future behavior of the controlled system under given objectives and constraints (cf. Richalet 1993). Further compared to simple control methods, such as PI controllers, MPC has the ability to anticipate future changes in the reference trajectory and handle large time delays and high-order dynamics. While most real processes are not linear, they can often be approximated by linear models over a small operating range. Linear MPC approaches are used in the majority of applications. When linear models are not sufficiently accurate to represent the real process nonlinearities, several approaches can be used, such as linearization techniques (cf. Rawlings 2000). Due to its algorithmic complexity and demand of process knowledge, MPC is still not state of the art for the control of production processes. However, if process knowledge is available, research results show the effectiveness of MPC for quality- and safety-oriented control of production processes (cf. Stemmler et al. 2019; Wu et al. 2019).

Data-driven modeling approaches Existing MPC approaches typically require the availability of a sufficiently accurate model to achieve desired closed-loop stability and performance guarantees. As there are often only uncertain system models available, MPC approaches allowing for an online adaptation or learning of the underlying model are of crucial importance. Fueled by the widespread success of machine learning, the question of how to beneficially employ learning techniques in the context of control has received an increasing amount of attention in recent years. Gaussian processes have been used to define and adapt online a continuous stirred-tank reactor model for MPC by Maiworm et al. (2021) and for autonomous racing by Kabzan et al. (2019). Similarly, neural networks are used to learn models for MPC in numerous applications, such as distillation columns (Vaupel et al., 2019) or laser beam welding (Bollig et al., 2003). Finally, Support Vector Machines (SVM) have, e.g., been used for predictive path tracking of autonomous vessels (Liu et al., 2021) and the control of a neutralization reactor in chemical plants (Lawrynczuk, 2016).

The maximum possible control performance of MPC is limited by the accuracy of the underlying process models. Identifying these models, especially for highly nonlinear systems, is a time-consuming and complex endeavor as most real systems are too complex to be fully described by physical models (Schoukens and Ljung, 2019). However, it is possible to derive an approximate system model by first-order principles with sufficient accuracy. Such models are known as white-box models.

Since most industrial processes are closely monitored, measurement data describing the processes is often available. This data can be exploited to create data-driven input/output models, so-called black-box models. While they have the potential of being universal function approximators, they often lack physical interpretability as they only map relations between system inputs and outputs.

Gray box models intend to combine the advantages of both models: data-driven methods estimate/predict parameters or system dynamics and, thus, augment white-box models based on process knowledge.

The aforementioned SVM represent a modeling technique with gray box ability. They come with great theoretical guarantees, such as globally optimal models without the risk of sub-optimal learning and favorable computational complexity for large feature spaces. The latter is often required for complex physical systems with multifaceted dependencies. SVM further map the given features into a larger dimensional space to fully explore the complex dependencies between the features. Thus, SVM are proficient at discovering unknown dependencies for dynamic modeling (Suykens, 2009).

At the same time, an additional computational expense for the larger dimensional space can be avoided by so-called kernel functions. Kernel functions preclude an explicit mapping of the features and instead operate directly on the target space (henceforth referred to as kernel space). Furthermore, specifications for the kernel function and kernel space allow for gray box modeling by pairing SVM with existing domain knowledge (Ay et al., 2019b). Hammerstein and Wiener's approaches further allow embedding of existing knowledge (Falck et al., 2009). Hence, in combination with fast solution methods (e.g., sequential minimal optimization (Ay et al., 2021) or least-squaresSVM (Liu et al., 2021)), SVM are highly suitable for online identification and MPC of systems with fast changing dynamic behavior.

Integrated, data-driven quality control Quality can be described in terms of workpiece quality (nonvolatile workpiece properties, e.g., workpiece surface quality or weld seam geometry) and process quality (volatile process properties, e.g., sustainability and economic efficiency) under appropriate process boundary conditions (e.g., materials and auxiliaries). Due to their physical mechanisms and interdependencies, production processes cannot be adjusted arbitrarily without violating basic process and machine limits such as stability boundaries. The moderation of the application requirements with the available process space thus describes the core challenge of process and workpiece quality. Model-based quality control approaches must therefore not only represent quality on the basis of available sensor data and digital shadows but also offer a control strategy that takes into account basic stability criteria. The first key component is the digital shadow for describing the workpiece and process quality on the basis of sensor data. Primary sensor data is characterized by high availability and is directly available at the production system. Secondary process data requires dedicated sensors, but directly describes the quality characteristics. The modeling effort of the digital shadow is, therefore, inversely proportional depending on the significance of the data available, e.g., the availability of sensor data instead of process data. The control strategy ultimately contains the methodical competence to control the process according to corresponding target conflicts on the basis of decisive and transient features. The production system finally receives the ability not only to control quality but also to provide usable quality data for the production network (Reisgen et al., 2019, 2020c).

Semantic Web and ontologies The challenge of creating machine-understandable data is addressed by techniques of the Semantic Web (Barbau et al., 2012). In essence, it enables the design of universally valid ontologies, a formal description how annotation data is structured, as well as an automatic annotation of data. While these technologies have long been a subject of research, there is still an ongoing discussion on their usability and appropriate use cases (Hogan, 2020). The common opinion is that these technologies have a huge potential, especially in domains like the IoT (ISO/IEC, 2018) or the IoP.

In the Semantic Web, formal ontology description and data storage is based on the Resource Description Framework (RDF), a data model standard developed by the World Wide Web Consortium (W3C) (Cyganiak et al., 2014). The RDF data model is represented as a directed graph, where each relation is a triple consisting of two nodes (subject, object) and an edge (predicate) linking them together. Every resource (subject, predicate, object) in RDF is formed analogously to the convention of URLs to ensure a worldwide unique identifier. The Ontology Web Language (OWL) (McGuinness and Van Harmelen, 2004) was developed on the basis of RDF and is used in the Semantic Web to describe ontologies.

The aforementioned fundamentals lay a methodological base for the further described approaches. The further described applications rely on these methods, though providing domain-specific solutions within different fields in production technology.

11.3 Domain Application

This section covers the three main subsystems of the control (cf. Fig. 11.2): data aggregation and sensors, model identification and optimization, and autonomous systems and decision support. The shop floor, consisting of machines and processes, marks the system to be controlled and is thus not covered in a single subsection. The covered approaches are domain specific and aim at explaining different solutions following the common idea of the IoP. These approaches mostly cover specific technological solutions at shop floor level (Sect. 11.3.4), but explicitly target model and data usage across shop floors and the IoP.

11.3.1 Data Aggregation and Sensors

While installation of new sensor systems is expensive, the machine tool itself has already a big variety of sensors integrated which can be sampled. Furthermore, connecting and utilizing multiple data sources arise different new challenges, namely, handling of redundant data or data with different frequencies. Another project targets the quality control after the manufacturing process, aiming for quality measurement of the workpiece directly on the machine.

Data acquisition and signal fusion When aggregating data from the shop floor, different sources are used to sample data from machines and processes. While machine tools have integrated sensors that can be used as data sources, commercial CNC controls have a large variety of interfaces, making it difficult to acquire data from different machines.

For the continuous acquisition of high-frequency data from machine tools, a middleware for commercial CNC controls was developed (Brecher et al., 2018), e.g., Sinumerik 840D sl and Mitsubishi M700/800. Machine internal data, including drive data, such as motor current, actual position, and spindle speed, as well as process- and control-related information, i.e., the actual tool number, the line number of the NC program, zero point offset, etc., is continuously captured in position control cycle (500–1000 Hz). Furthermore, the trace software is extendable to synchronously sample signals from external sensors, for example, thermistors and piezoelectric sensors. For lower-frequency dimensional data, data acquisition using standardized Open Platform Communications Unified Architecture (OPC UA) interfaces to machine data can be sufficient. OPC UA interfaces exist for a multitude of machine controllers. Machine data are read from the machine control system which is realized here by using an edge computer (Brecher et al., 2018) which transfers the information into a downstream data infrastructure consisting of the publisher/subscriber protocol Message Queuing Telemetry Transport (MQTT) as illustrated by Sanders et al. (2021). Sustainable data collection and storage are essential for future reuse and analyses (Bodenbenner et al., 2021a). Hence, machine information is annotated with metadata using a defined data syntax that can be automatically structured and stored in a database (Bodenbenner et al., 2021b), laying the groundwork for sustainable data storage according to FAIR data principles (cf. Sect. 11.3.4). Sample rates of machine internal data are usually limited to the abovementioned 1000 Hz.

However, some applications require data with higher sampling rates. During rough machining in milling, e.g., the process forces determine productivity and product quality (Liang et al., 2004). Typical approaches for monitoring process forces still mostly rely on piezoelectric dynamometers. These are costly and reduce the stiffness of the tool-machine system, making them nonoptimal candidates for usage in industrial environments. As an alternative, motor current of the machine tool's feed drives can be used as a soft sensor for indirect force measurements as it is directly proportional to the motor torque (Miura and Bergs, 2019). However, current signals of feed drives can have low sample rates, be noisy, and be of varying quality and, thus, require sensor fusion of different signal sources to obtain a more stable signal. At the core of the sensor fusion, the spindle provides a high-quality signal as it has a constantly high speed. External sensors with sample rates of 50 kHz are integrated in the motor power circuit and sampled on different real-time devices to include high process dynamics.

In practice, the fusion can be realized using a Kalman filter which implements a system model and continuously corrects this model based on signal quality, while it is itself optimized through experiments (Schwenzer, 2022). Following the differentiation of signal fusion according to Hall and Llinas (1997), this can be considered on the second level, as the information needs to be transformed to a common coordinate system as well as put into relation using force models. The resulting high-quality signal is then used to identify models of the process at run-time. To use this in closed-loop systems (cf. Sect. 11.3.3), one main challenge is that the sensor data needs to be provided with low latencies to allow for fast responses. Process-near sensor processing is best suited for this purpose and, additionally, Time-Sensitive Networking (TSN) can help to ensure the low latencies. However, additional challenges arise as soon as the process control is moved to remote locations. Here, novel in-network computing approaches might provide a suitable middle ground as reasonably expressive computations (Kunze et al., 2021) as well as simple control functionality (Rüth et al., 2018) are possible on networking devices.

On-machine measurements Common quality management measures for inspecting specification and tolerance compliance often involve transporting workpieces into climate-controlled measurement rooms, acclimatization periods, and dimensional measurements on Coordinate Measuring Machines (CMMs). A number of standards exist to enable traceable measurements that are, e.g., required for safety-critical applications and part certification. ISO standards 10360 and 15530 define ways to analyze the measurement uncertainty of CMM measurements accounting for a multitude of influences.

With on-machine measurements, the workpiece's geometry is measured with the machine tool's probing system itself after material removal and in the original clamping situation. Advantages are immediate feedback on dimensional accuracy allowing for direct rework while significantly reducing the number of necessary production steps compared to CMM measurements in a measurement room (Sanders et al., 2021). To create reliable workpiece measurements on the same machine, the workpiece was machined on geometric and thermoelastic machine and workpiece errors need to be accounted for. Thus, aforementioned uncertainty analyses and corresponding modeling approaches for error compensation of machine (Dahlem et al., 2020) and workpiece deformation are required. Current work within ISO/TC 39/SC 2 aims at translating CMM-specific measurement definitions for machine tools into an additional technical report part 13 for ISO 230.

To illustrate the relevance of the said topic, Emonts et al. (2022) performed an experimental analysis of thermoelastic deformation of an example turbine housing. They simulated machining heat influx by attaching heat pads to the workpiece, increasing local workpiece temperature by 30 K and average temperature by 15 K. Results showed a part diameter increase of approx. 500 µm (nominal approx. 1400 mm), e.g., twice the expected diameter change, assuming homogeneous temperature distribution and linear thermal expansion with average part temperature.

11.3.2 Data-Based Model Identification and Optimization

For controlling of production processes, the usage of different data sources alone is not sufficient. Sensors are noisy and systems may change quickly. Online model identification and model optimization enable consideration of system changes and extend the range of the validity of models. This subsection covers research in online force model identification in milling as well as model optimization in the condition monitoring of ball screw drives.

Online model identification Model-based control systems require online identification to account for changes within the systems, which can occur in both, the machine and the process. Models need to be as simple as possible while remaining as precise as necessary to suffice the usage within control systems. Milling is a highly flexible process resulting in constantly changing engagement between tool and workpiece and, as a result, nonlinearly changing process forces. The relation between geometrical engagement of tool and workpiece and process forces is modeled using the force model according to Kienzle (1952). The coefficients of the Kienzle model are identified using engagement simulation data from the process planning phase and the fused force signals from the motor currents (cf. Sect. 11.3.1). As the Kienzle model is nonlinear and nonobservable, an ensemble Kalman filter is used as a nonlinear observer to enable an instantaneous model identification in one step (Schwenzer et al., 2020). This approach allows usage of a simple force model to account for changes in the manufacturing process, instead of trying to apply a very specific model for each process beforehand. The identified models can be shared in the IoP and reused as a starting point for future identifications.

Regarding the machine tool, SVM are utilized to identify the unknown behavior of the drives and enable model-based controllers like MPC to accurately forecast the future engagement of the tool while maximizing its velocity (Ay et al., 2019a). The data lake can thereby be deployed for an initial identification as it can be searched for already existent data from a comparable process. Thus, no additional resources (time and personnel) have to be expended for model identification experiments. The data lake models are then tailored to the present process online by SVM and sensor-acquired data, with aforementioned methodologies for gray box modeling and efficient online identification (Ay et al., 2021).

The implicit data selection of SVM also has positive implications for data processing and memory efficiency. SVM assess the importance of every data sample for the resulting model to the extent that irrelevant data samples are excluded. Therefore, the limited memory during the process can be utilized more efficiently only for the relevant subset of data. Furthermore, when new sensor-acquired data emerges and the memory runs at limit, SVM offer two measures to reach a decision about which data to exclude from memory in favor of new data: (i) the model weights of SVM for the aforementioned assessment of data relevance and (ii) the evaluated kernel function of SVM. The latter determines the similarity between data samples for correlation-based kernel functions. Thus, the most expendable data samples can be determined as those with low relevance for the resulting model and high similarity to already existing data samples.

However, the utilization of the initial models from of the data lake is not sufficient in an application for forecasting within MPC. Heuristic methods are thereby combined with robust optimization to automatically tune the controller and its soft sensors. Thus, no additional configuration of the controller is needed at shop floor level. A suitable method for this purpose is Bayesian optimization as it can consider model uncertainties due to later model adaptation/optimization (Stenger et al., 2020).

Overall, the presented technologies enable a closed data cycle: Information from the data lake can be used for the initial deployment of the model-based quality control of the process. Subsequently, sensor-acquired data helps the model-based control framework to self-optimize during the process. Finally, the newly optimized models are fed back to the data lake, including relevant data and production context.

Model optimization for condition monitoring of ball screw drives The availability of production facilities and equipment plays a decisive role in the competitiveness of manufacturing companies under the increasing pressure of globalized markets, with a particular focus on reducing downtimes due to unplanned maintenance activities to ensure sustained high productivity (Bullinger et al., 2008; Schapp, 2009). The inclusion of empirical knowledge regarding the service life of machine components and tools cannot generally be included in maintenance planning, as there is usually a large variance in the components to be manufactured. The resulting conflict of goals between the reduction of non-value-creating activities (through reactive maintenance) and the avoidance of unplanned downtimes (through preventive maintenance) represents a major challenge (Wloka and Wildemann, 2013). The component load is directly linked to the feed axis forces of a machine tool, which for their part correlate with the manufacturing productivity. The poor accessibility of components within the machines leads to comparatively high costs and long downtimes for maintenance work (Brecher et al., 2008). The analytical prediction of the service life of ball screws is based on calculations according to the standards (DIN/ISO, 2011), which are based on findings by Weibull as well as Lundberg and Palmgren. The service life L_{10} (number of revolutions) with an occurrence probability of 90% is calculated on the basis of empirically determined equations (Lundberg and Palmgren, 1949; Weibull, 1949):

$$L_{10} = \left(\frac{C_{\text{dyn}}}{F_m} \right)^3 \cdot 10^6, \tag{11.1}$$

where C_{dyn} is the dynamic load rating and F_m is the equivalent axial load.

Due to the non-consideration of decisive influencing factors, such as the stroke length, manufacturing deviations of components, additional loads due to assembly errors, and the unknown loads occurring during operation, the calculated and the actual service life match only in 20% of the cases. Denkena attributes this, among other reasons, to the fact that the service life calculations do not offer the possibility of taking into account the usage history of a system (Denkena et al., 2009). This highlights the need to develop new concepts for forecasting component failures.

Machine data of real processes, which are continuously available within the framework of the IoP, contain the potential to increase the availability of plants and to ideally plan necessary maintenance work by using the knowledge implicitly included in the data. The procedure for achieving this goal is divided into two parts: (i) Determination of the current machine condition on the basis of historical operating data, which can be extended with condition indicators obtained from reference runs. (ii) Prediction of the usage-dependent development of the machine condition based on the current condition and the assumption of a future usage profile. Since in the literature the feed axes of machine tools, and, in particular, the linear guides and ball screws, are identified as the cause of machine downtimes, the IoP will pay particular attention to these components. From the recorded data of the motor current, the effective feed force can be calculated in a first approximation for a horizontally installed feed axis with a ball screw (Brecher et al., 2020):

$$
\begin{aligned}
I \cdot k_T \approx T_{F,\text{input side}} &+ \frac{1}{i}\left(T_{F,\text{output side}} + \frac{h}{2\pi}(F_P + F_F)\right) \\
&+ 2\pi\dot{n} \cdot \left(J_M + J_{G,\text{input side}} + \frac{1}{i^2}(J_{G,\text{output side}} + J_{Sp} + J_T)\right),
\end{aligned}
\tag{11.2}
$$

where F_P/F_F denotes the process/friction force, h the spindle pitch, n the motor speed, i the gear ratio, I the (torque-forming) motor current, J_G the gearbox inertia (input side, output side), J_{SP} ball screw inertia, J_M/J_T the motor/table inertias, k_T the torque constant, and T_F the frictional torque (input side, output side).

The necessary compensation of inertial and frictional forces requires different model depths depending on the design of the feed axis. These depend on the different designs of gearboxes, linear guides, and other machine components or disturbing influences (Brecher et al., 2020). In a first step, this procedure enables service life calculation and prognosis on the basis of historical load data and service life models according to the state of the art (Munzinger and Schopp, 2009; Huf, 2012).

Since known models are simplified in their complexity by assumptions made and thus reduced in their prognosis quality, several model extensions were developed. This allows load distributions within machine components to be calculated in a process-parallel manner as a function of geometry, material, and load parameters, so that a discrete-position service life calculation can be carried out. The model extensions described by Brecher and Biernat allow the consideration of load data determined in parallel with the process as well as further meta-information, including spindle pitch errors and the tolerance class of machine components.

The influence of the tolerance class and the stroke length on the service life can be specified as up to 30%. Relevant models are presented in detail in Brecher et al. (2020, 2021a,b,c), among others. Figure 11.3 shows the example transfer of traced data into a position- and force-resolved representation of fatigue-relevant load cycles. The availability of data from production and test benches, which are obtained in the context of the IoP, enables a cross-domain validation as well as further development of the reduced models according to requirements under real operating conditions. Finally, these models will be used to implement a prognostic maintenance planning with significantly improved quality.

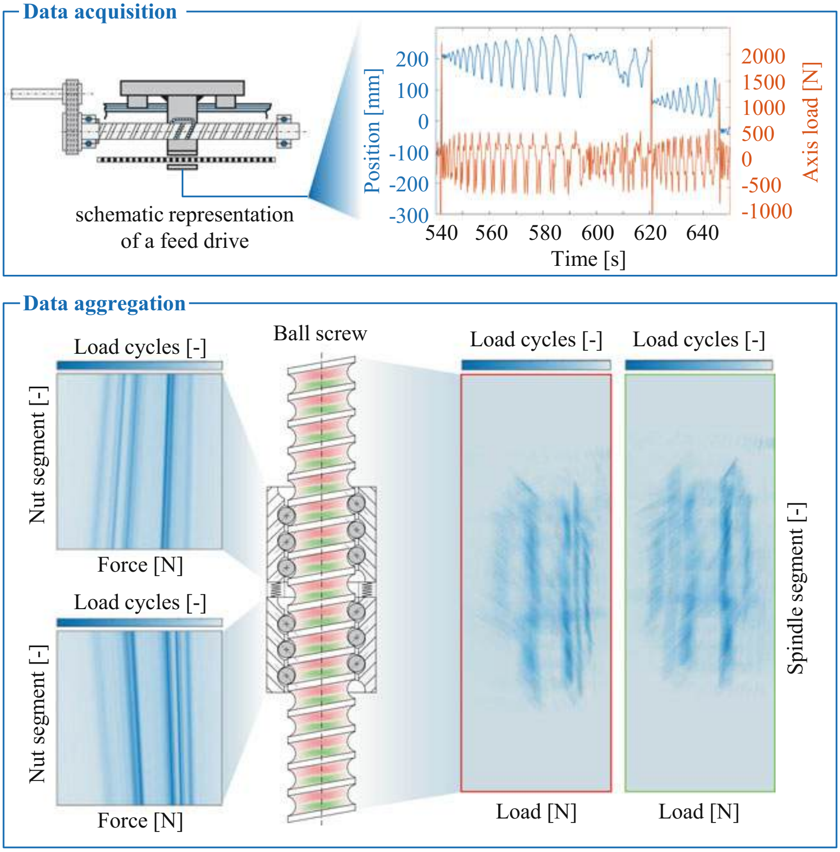

Fig. 11.3 Transfer of a time series into matrix notation (Brecher et al., 2021b). (With kind permission of wt Werkstatttechnik online)

11.3.3 Autonomous Systems and Decision Support

The main objectives to enhance production processes are improving productivity and reducing tool wear while maintaining part quality and process safety. Data acquisition and model identification are necessary steps to apply autonomous systems in production processes. However, to close the control loop, data and models also need to be utilized in autonomous systems or for humans as decision support. The IoP delivers an infrastructure for sharing models and data, but the application remains at shop floor level. This section addresses autonomous systems and methods for decision support, using previously acquired data (cf. Sect. 11.3.1) as well as identified and optimized modeling techniques (cf. Fig. 11.3.2). The foci, however, target objectives at manufacturing level, including workpiece quality, tool wear, process safety, and improvement of productivity.

Workpiece quality monitor The workpiece quality is one of the most relevant indicators for machining production in milling. Errors in machining processes can be traced back to one of the following root causes: static, transient, and dynamic geometric errors as well as tool errors (see Fig. 11.4): (i) Static geometric errors are inherent to all mechanical platforms and are caused by imperfections in mechanical structures, guide systems, encoder systems, and numerical uncertainties. After calibration, modern machine tools allow for control-based compensation which significantly reduces said errors. (ii) Tool errors are caused by tool manufacturing imperfections and tool wear over time. While initial tool dimension errors can be measured and compensated for, tool wear over time must be predicted based on models and data. (iii) Transient thermal errors are caused by (inhomogeneous) thermal states in machine tool and workpiece and their respective thermoelastic deformation. While assumed homogeneous, linear thermal expansion can be compensated for, complex thermal deformation prediction in real time is an area of active research. Relevance of thermal errors increases with the ratio between required tolerances and part dimension. Thus, their importance increases for precision manufacturing and large workpieces. (iv) Dynamic errors in machine tool and workpiece are caused by acceleration, forces, and control system inaccuracies resulting from the machining process itself.

To analyze the workpiece dimensional accuracy, the machine's internal probing system is used to probe the workpiece (cf. Sect. 11.3.1). In order to estimate the workpiece surface quality, such as straightness or flatness, high-frequent process data and machine dynamic models are mandatory (Königs and Brecher, 2018). In the so-called process-parallel material removal simulation, the relative position between the workpiece and cutting tool is calculated from the encoder signal, which is continuously sampled by a middleware described in Sect. 11.3.1. When the tool intersects the workpiece, the corresponding volume will be removed. Random errors caused by component wear, controller deviation, or material inhomogeneity are already contained in the encoder data. To determine the actual position of the tool center point, systematic errors, such as geometric-kinematic accuracy and force-induced tool deformation, still need to be accounted for. While the former can be compensated for by means of volumetric compensation based on machine calibration data, the latter requires knowledge of axis and tool stiffness, and cutting force. For this purpose, a real-time-enabled force model is developed by Fey et al. (2018), which is driven by process-parallel trace data. Machine and workpiece stiffness are either identified experimentally or simulated by finite element analysis. Thus, the real cutter engagement location is determined.

After the manufacturing process, a virtual measurement is performed based on the resulting virtual workpiece. Straightness, roundness, or surface flatness are evaluated by extracting the points on the measurement path from the point cloud. Negative trends regarding quality tolerances can thereby be detected immediately

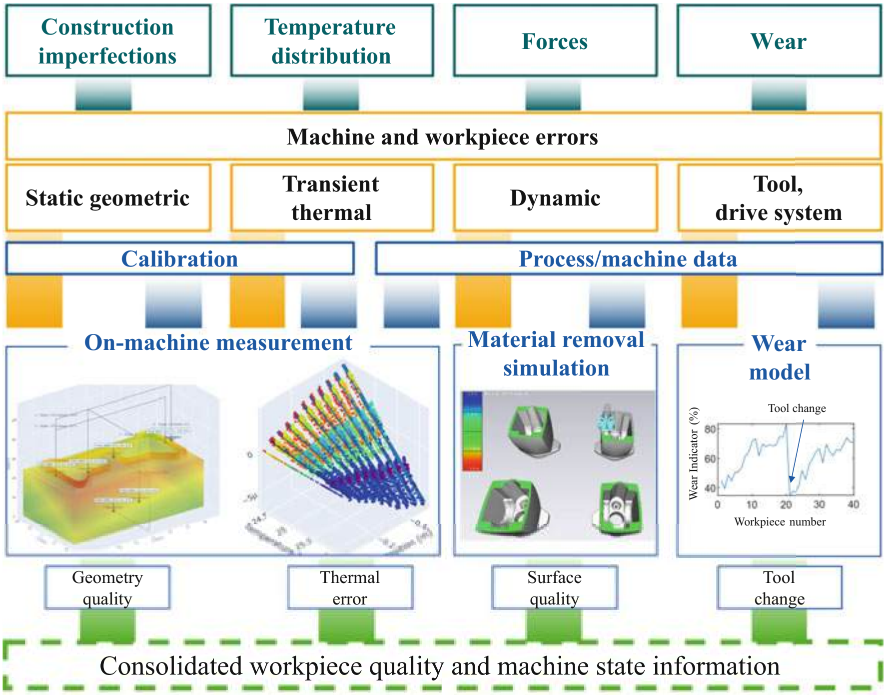

Fig. 11.4 Data-driven workpiece quality and machine state monitor: Multiple influencing factors reduce workpiece quality and degrade machine performance over time. A set of complementary applications predicting and, thus, enabling correction are presented. As a future step prediction, output of said models can be combined to an overall machine state and workpiece quality

after the manufacturing process, which enables a quick and reliable quality feedback loop.

Tool life monitor The prediction of the optimal timing for tool change is essential for automated mass production, as this is directly associated with the machine-idle time and workpiece quality. Without further monitoring sensors or signals, a very conservative tool changing timing has to be selected due to the complexity of the machining process and numerous random influences in manufacturing. Thus, the main challenge of tool monitoring is providing a practical and reliable solution at shop floor level.

Our proposed tool monitor approach only bases on internal machine data, i.e., no additional sensors such as Charge-Coupled Device (CCD) cameras or dynamometers are required (Xi et al., 2021). To achieve a robust estimation of the tool condition, we adopt multiple built-in sensors and signals, creating a multi-domain evaluation. More specifically, the estimated cutting force, the spindle current, and the spindle speed are fused together to create a wear indicator. Using the aforementioned trace solution in Sect. 11.3.1, it is possible to automatically recognize which cutting tool is used and when it is used, identified by tool and NC line numbers. Followed by a wear model, which outputs a wear indicator for each cutting task, a tool wear progress chart can be generated. For roughing processes, as long as the indicator does not exceed the threshold, the roughing tool is assumed to be sufficient. However, for fine finishing processes, even medium tool wear could already affect the final surface quality. Thus, a comprehensive consideration of the wear indicator combined with the quality indicator is necessary. By utilizing the virtual quality inspection introduced above, the maximum lifetime of the cutting tools can be safely approached by means of a statistically controlled process.

Force control in milling The high flexibility of the milling process results in constantly and abruptly changing engagement conditions between tool and workpiece. By using mechanical force models, such as the Kienzle model, the relation between tool-workpiece engagement and process force is modeled. Model parameterization is usually based on literature values, which have been identified once for specific combinations of tool and workpiece materials assuming constant tool conditions and homogeneous material. Using online model identification approaches (cf. Sect. 11.3.2) and a material removal simulation, changes in the system due to tool wear or material inhomogeneity can be accounted for. However, the changing engagement results in a highly dynamic and nonlinear behavior of the process forces which is difficult to grasp for conventional fixed-law controllers. As a consequence, these controllers typically fail at providing a stable force control. In contrast, more sophisticated control approaches can adapt models at run-time and account for the inherent nonlinear behavior of milling. To account for the changing process models in milling, an MPC is used to control the process force as it can predict the short-termed future and, therefore, account for abrupt system changes before they actually occur (Schwenzer, 2022). At the same time, MPC is able to respect safety critical constraints of the process while maximizing productivity.

Fume emission rate control Gas Metal Arc Welding (GMAW) is one of the most frequently used industrial welding processes as it has broad applicability with a wide variety of joining partners, high scalability, as well as low process and system costs. Nevertheless, arc-welding processes involve considerable physiological risks. In addition to process-related noise and strong IR and UV emissions, welding fume emissions have currently come increasingly to the fore. In 2018, the United Nations International Agency for Research on Cancer categorized welding fumes as carcinogenic. Consequently, minimization of Fume Emission Rates (FER) as a crucial physiological and sustainable process quality is a central task of modern GMAW development.

In experimental investigations, it has been observed that a characteristic curve of the welding fume emission is formed via the welding voltage (Quimby and Ulrich, 1999; Pires et al., 2010). In particular, correlations to the FER could be identified in process features of electrical and optical time series by Reisgen et al. (2020a,b). To generate a digital shadow of the FER, a dataset consisting of 273 welded process

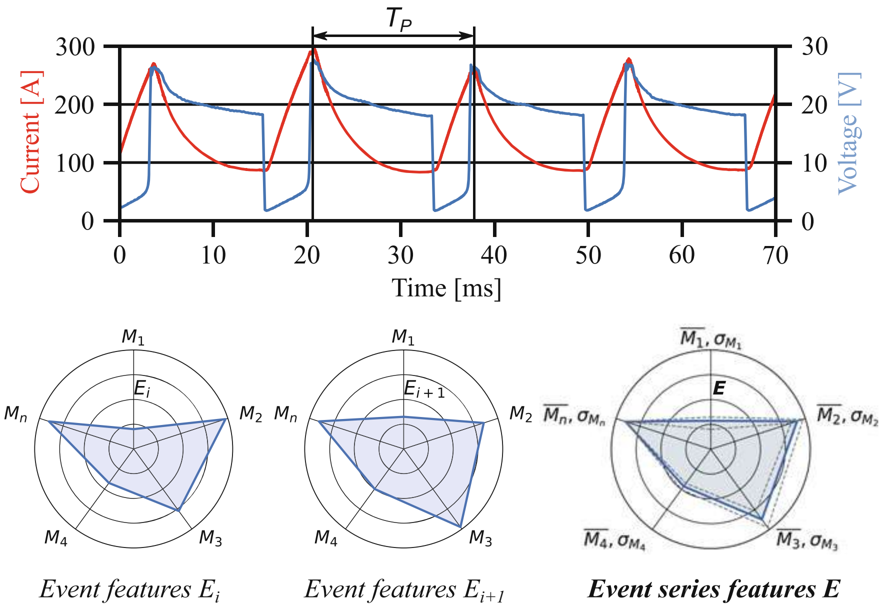

Fig. 11.5 Feature engineering for electrical GMAW time series data; top: electrical GMAW time series with periodicity TP; bottom: gathering single event features E_i to build one significant event series feature set E

parameters with high-resolution time records (200 kHz) from welding voltage and welding current was recorded. To label the time series with an according quality feature, the FER was simultaneously measured according to DIN EN ISO 15011-1. The process variables welding current and welding voltage can be recorded directly at the process and are thus characterized by high availability, which, however, also requires a high degree of interpretation and modeling with regard to the FER. For this purpose, time series can first be converted into feature vectors. The GMAW process is often characterized by a stochastic but also periodic material transition (e.g., short circuiting transfer in Fig. 11.5). This periodicity can be used to derive significant features over each process period. With each additional feature vector and the associated period duration, a feature vector series is created. The result is a feature vector time series with equidistant feature vectors for constant period durations or an irregular sequence if the period durations are based on stochastic process events, e.g., for short circuiting transfer in Fig. 11.5. On the basis of these vector series, statistical features such as mean values or standard deviations can be formed, which can make a reliable statement about the process characteristics.

This significant feature vector was thus linked to each FER label and used for supervised learning. The model generation process, in addition to achieving a sufficiently accurate model, was also aiming to reveal correlations for the consecutive control strategy. The concept of data-driven quality control for welding will

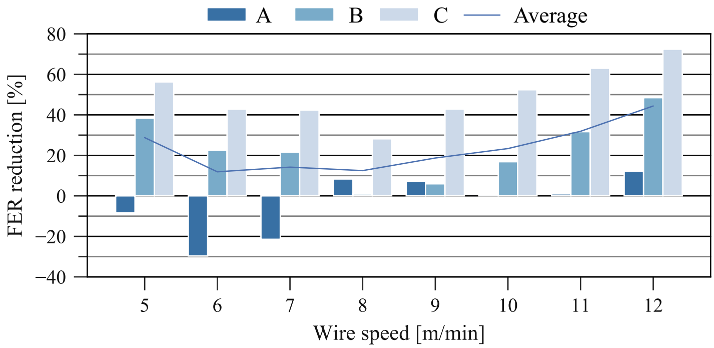

Fig. 11.6 FER minimization potential with data-based quality control at different process working points (A, B, and C)

contribute to the comprehensive acquisition of connected quality data. Nevertheless, the quality model or digital shadow must first rely on conventional process data often collected in the laboratory. However, typical laboratory tests only allow for a limited scope of experiments, which contrasts with the required datasets for deep learning. Nevertheless, with the manageable dataset used here and the feature engineering described, it was possible to show that high model accuracies are possible (Reisgen et al., 2020a). In particular, the XGBoost algorithm (Chen and Guestrin, 2016) was able to achieve high results with an $R^2 = 0.89$ on the test dataset. In contrast, conventional statistical modeling via multiple linear regression resulted in poorer model quality ($R^2 = 0.80$), but led to the necessary system transparency on which the control strategy could be built.

By investigating correlations, using multiple linear regression models, two FER minima were found in the data. After comparison with the basic process stability, a control system was implemented, which adapts the current process working point to the next FER minimum within 1 s. The control loop was therefore closed, using distinct time series features and welding voltage correction parameters on the welding power source.

Figure 11.6 clearly shows that the welding fume emission as a decisive process quality can be reduced by an average between 12 and 45 percent, starting from three operating points. The optimization was carried out via the voltage correction, which, however, also influences the weld geometry. The resulting trade-off between different quality features must be considered here depending on the application. Finally, and in addition to this control application, the FER can be extracted directly on the welding system and without costly FER measurements in accordance with DIN EN ISO 15011-1, thus accessing an essential sustainable process characteristic.

With this approach, data-driven models in the sense of the digital shadow are applied on the one hand to solve domain-specific challenges. On the other hand, the welding system is empowered as a source of aggregated data and thus provides a valuable contribution to the data lake and cross-domain applications.

11.3.4 Model and Data Integration in Connected Job Shops

Distribution of models over different machines and even different job shops within the IoP requires common semantics. Heterogeneous data are combined using ontologies, including information from other domains, like process planning (cf. [Resilient Future Assembly Systems Operation in the Context of the Internet of Production]) or quality assurance. This section describes an approach to ontologies using Blade-Integrated Disk (BLISK) manufacturing as an example.

A BLISK is an integral rotor component, which combines disk and blades within a single component. It is used in the compressor of modern turbo engines. The manufacturing of such components represents one of the most challenging tasks in turbomachinery manufacturing (Ganser et al., 2022). The extremely tight tolerances put highest demands on product and process design. To efficiently achieve the required tolerances, the topics of model and data integration in BLISK manufacturing are of high importance.

Model integration refers to the integration of process models into a Computer-Aided Manufacturing (CAM) system to extend the digital shadow of a BLISK. Models include, e.g., a macroscopic engagement simulation based on a multi-dexel model (Minoufekr, 2015), an analytical model to calculate the microscopic engagement data (uncut chip geometry) (Cabral, 2015), a dual-mechanistic cutting force model (Altintas, 2012), and a model to predict tool and workpiece deflections. This information is stored in the digital shadow and used to optimize the process design (Fig. 11.7).

Data integration aims to develop possibilities for systematic and efficient storage of simulation, process, and product data along the product and process development chain. It also aims to connect data stored in different systems and annotate it with meta information by developing an ontology to describe the meaning of the metadata.

Data generated during product and process development steps is stored in various data formats, e.g., in .stp, .igs, or .stl files for the design step (CAD), odb or .csv files for the process design (CAE), and .nc or .mpf files for CAM. However, the semantic meaning of the data is only understandable by experienced or trained employees and

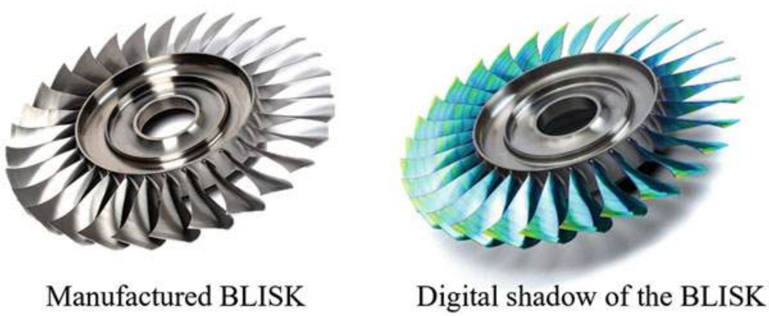

Fig. 11.7 A picture of a BLISK and its digital shadow

just in some cases understandable by machines. In general, data integration can be divided into three parts (Schiller et al., 2022): (i) The definition of an ontology that describes the relations and semantic meaning of the data. (ii) Adapting existing data into appropriate structures following the ontology, or adding additional metadata to the existing data so that it can be linked using the ontology. (iii) The formal storage of the data, e.g., using an information management system that centrally manages the data and can check the correct semantic description of new data. While the last two steps are strongly influenced by a technical implementation, the creation of an ontology requires a deep domain knowledge and a clear formal definition. For BLISK manufacturing, an ontology was defined using OWL (McGuinness and Van Harmelen, 2004), describing the core relations between the generated datasets in the individual steps of the product and process development chain. Figure 11.8 shows the structure and main core classes and properties for each of the four steps (CAD, CAM, CAE, CNC).

To structure the ontology, it is divided into four parts. For each featured process chain step, we define a single ontology namespace: The BLISK schema, the CAM schema, the milling simulation schema, and the manufacturing schema. For each schema, a core class was defined. Additional properties enabled to link the classes and create a knowledge graph connecting all four steps. The BLISK schema is related to the product design step. The core class is the BLISK, which is a subclass of a geometry model, from the CAM schema. The core class of the CAM schema is the milling operation class. The milling operation rules a milling process. The milling process class enables the connections between the CAM, CAE, and CNC step. The milling process which is described by this CAM operation can be a simulated milling process, defined in the simulation schema or a real milling process running on a machine, defined in the manufacturing schema. A graph like this can be extended with additional classes and relations. This makes it possible to append all the data that is generated in the steps of the product and process development chain to an entire knowledge graph, thus enabling complete data integration. This methodology, exemplary shown for BLISK manufacturing, can be used for sharing data and models across job shops and the whole IoP.

11.4 Conclusion and Outlook

This chapter gave an overview over the current research in model-based controlling approaches for production processes in the IoP. The chapter has been following the different subsystems necessary to control machine tools and production processes: data aggregation, model identification and optimization, and autonomous systems and decision control. A common usage of data and models connects machines, job shops, and the WWL. The individuality of different manufacturing processes results in domain-specific problems and, therefore, particular approaches in the different fields. However, a common ground lies in the methodical approaches, utilizing data as well as expert knowledge. Potentials for future research lie, e.g., in automated data selection from the data lake based on ontologies, such that the

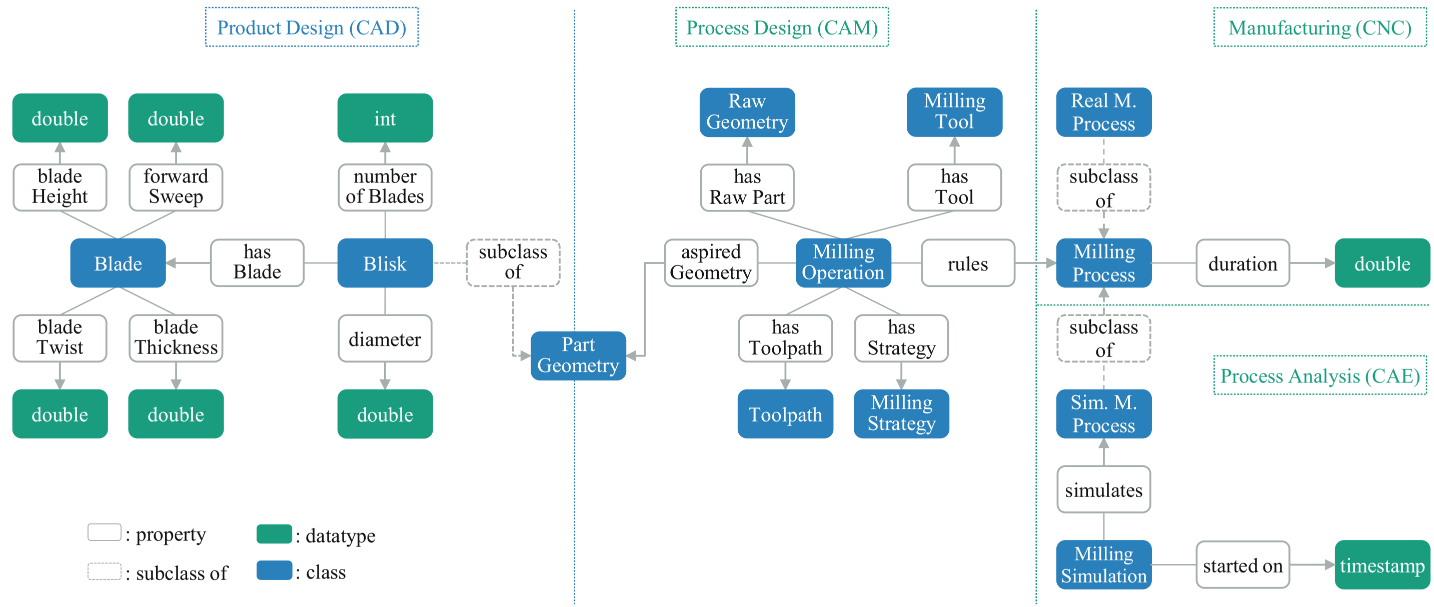

Fig. 11.8 The core part of the ontology for the PLM of BLISK manufacturing

processes can go online within the WWL. Furthermore, a greater formalization of the domain knowledge has the potential to further generalize the application of the presented methodology and thus allow symbioses between different domains. More methodically: New data-driven modeling approaches have to be considered due to their different strengths, like long short-term memory (Long Short Term Mmemorys (LSTMs)) networks. LSTMs are recurrent networks and well suited for mapping time-varying dynamics, especially. Following additional modeling approaches and the aforementioned abstracted domain knowledge, the applicability of the control approaches should be improved for more generic models. In addition, the setup of the controllers should be further automated to at some point reaching a near plug-and-play capability. The main challenge regarding the connection of job shops in the future is the connection of different manufacturing technologies as they usually appear consecutively during the production of components. Especially domain knowledge, which remains essential to automate systems, is highly focusing on single manufacturing processes and does not include interconnections between them. Digital shadows need to able to apply technology-specific data and models in a way that other domain experts and even users of produced components are able to utilize them. The IoP has the potential to achieve these connections, but remains rather visionary yet. The current works aim at closing the gaps between the technologies and will further continue in doing so.

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Improving Manufacturing Efficiency for Discontinuous Processes by Methodological Cross-Domain Knowledge Transfer

12

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Abstract

Discontinuous processes face common tasks when implementing modeling and optimization techniques for process optimization. While domain data may be unequal, knowledge about approaches for each step toward the solution, e.g., data gathering, model reduction, and model optimization, may be useful across different processes. A joint development of methodologies for machine learning methods, among other things, ultimately supports fast advances in cross-domain production technologies. In this work, an overview of common maturation stages of data-intensive modeling approaches for production efficiency enhancement is given. The stages are analyzed and communal challenges are elaborated. The used approaches include both physically motivated surrogate modeling as well as the advanced use of machine learning technologies. Apt research is depicted for each stage based on demonstrator work for diverse production technologies, among them high-pressure die casting, surface engineering, plastics injection molding, open-die forging, and automated tape placement. Finally, a holistic and general framework is illustrated covering the main concepts regarding the transfer of mature models into production environments on the example of laser technologies.

Increasing customer requirements regarding process stability, transparency and product quality as well as desired high production efficiency in diverse manufacturing processes pose high demands on production technologies. The further development of digital support systems for manufacturing technologies can contribute to meet these demands in various production settings. Especially for discontinuous production, such as injection molding and laser cutting, the joint research for different technologies helps to identify common challenges, ranging from problem identification to knowledge perpetuation after successfully installing digital tools. Workstream CRD-B2.II "Discontinuous Production" confronts this research task by use case-based joint development of transferable methods. Based on the joint definition of a standard pipeline to solve problems with digital support, various stages of this pipeline, such as data generation and collection, model training, optimization, and the development and deployment of assistance systems are actively being researched. Regarding data generation, e.g., for the high-pressure die-casting process, data acquisition and extraction

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approaches for machines and production lines using OPC UA are investigated to get detailed process insights. For diverse discontinuous processes and use cases, relevant production data is not directly available in sufficient quality and needs to be preprocessed. For vision systems, ptychographic methods may improve recorded data by enhancing the picture sharpness to enable the usage of inline or low-cost equipment to detect small defects. Further down the pipeline, several research activities concern the domain-specific model training and optimization tasks. Within the realm of surface technologies, machine learning is applied to predict process behavior, e.g., by predicting the particle properties in plasma spraying process or plasma intensities in the physical vapor deposition process. The injection molding process can also be modeled by data-based approaches. The modeling efficiency based on the used amount of data can furthermore be effectively reduced by using transfer learning to transfer knowledge stored in artificial neural networks from one process to the next. Successful modeling approaches can then be transferred prototypically into production. On the examples of vision-based defect classification in the tape-laying process and a process optimization assistance system in open-die forging, the realization of prototypical support systems is demonstrated. Once mature, research results and consequent digital services must be made available for integrated usage in specific production settings using relevant architecture. By the example of a microservice-based infrastructure for laser technology, a suitable and flexible implementation of a service framework is realized. The connectivity to production assets is guaranteed by state-of-the-art communication protocols. This chapter illustrates the state of research for use-case-driven development of joint approaches.

12.1 Introduction

Increasingly higher customer demands and smaller failure tolerances on produced parts challenge manufacturers in high-wage countries and call for innovations to remain competitive on international markets (Brecher et al. 2011). In recent years, digitization and digitalization in various manufacturing domains are being explored as very promising to raise overall production efficiency, may it be due to further automation or deeper understanding of the process. Especially, vast amounts of recorded data may offer great potential for elaborated analysis and improvement. However, in most cases, these data are scattered, often not even within the same databases, or not as numerous as needed for detailed data-based analyses (Schuh et al. 2019). In a so-called "Internet of Production," these issues shall be resolved by a new approach: Data, models, and methods, even from different domains, are made available by executing a developed ontology to connect these different aspects of knowledge. A new level of cross-domain knowledge exchange and possible collaboration will then be possible.

Discontinuous production processes may benefit from these developments. Discontinuity is on the one hand related to the state of operation: The herein considered processes in accordance with DIN 8580 produce product in batches with planned iterations of process steps, which is the definition of batch production. On the other hand, variables of state involved in the discontinuous process show a time-dependent variation of their values, depending on the state of the production, e.g., cavity pressure curve in injection molding. On the contrary, for thermodynamically continuous processes the variables of state should be kept constant at all times, e.g., extrusion.

A recurring challenge for discontinuous processes is the minimization of non-value-adding activities, e.g., when setting up the process, and the complexity to repeatedly find a balanced process under new circumstances and new production asset configurations. As these minimization tasks can be found similarly in all discontinuous productions, sharing of knowledge between domains may significantly raise the process efficiency and productivity.

In the following, challenges and potentials from the current state of the art for representative discontinuous processes are presented based upon a common procedure when modeling discontinuous processes. Detailed explanations regarding the use-case-driven development are given in subsequent subchapters dealing with the demonstrator processes. Various steps in this procedure are described in detail, and current research toward knowledge sharing is presented to give an understanding about possible method-based cross-domain collaborations.

12.2 Common Challenges in Modeling and Optimization of Discontinuous Processes

A process may be defined as the entirety of actions in a system that influence each other and which transport, convert, or store information, energy, or matter (N.N. 2013). In the cluster of excellence "Internet of Production," a variety of discontinuous processes regarding different production technologies are being researched

- High-pressure die casting
- Automated tape placement
- Thermal spraying
- Physical vapor deposition
- Injection molding
- Open-die forging
- Laser ablation, drilling, and cutting

An intermediate objective for every single process is the support of recurring production tasks, e.g., by assistance systems. Some process technologies such as injection molding qualify for an assistance system development due to their high grade of automation and advanced controllability regarding process stability. Less digitally progressed, less widespread, or highly specialized technology facing challenges regarding process understanding and controllability can benefit from methodological exchange for asset connectivity, correlation identification, sensor development, and other support processes on the road to sophisticated assistance systems. However, all processes may benefit from a general approach for digital and data-based methods in terms of Industry 4.0 to improve the processes efficiently as advocated by the "Internet of Production" (Schuh et al. 2019). Successfully probed methods in a specific domain for common tasks such as process setup, quality supervision, or continuous optimization should be considered candidates for a cross-domain knowledge sharing to pool competency and drive intelligent processes. An abstracted and common sequence of tasks for data-based, digital development of discontinuous processes, directly connected to the maturation of assistance system development in respective process technologies, supports the methodological collaboration. This approach is illustrated in Fig. 12.1.

Each approach for a digital and data-based problem resolution (see Fig. 12.1) starts with a sharp problem identification and the definition of concerning information. In the best case, quantifiable parameters containing this information are already known, measurable, and available. Modern production systems are characterized by their reliance on a multitude of sensors and programmable logic controls. Measurement and input values are processed by the control system and the physical entities of the machinery are actuated accordingly. Technically there is no shortage of process data. However, due to the diversity of discontinuous production processes

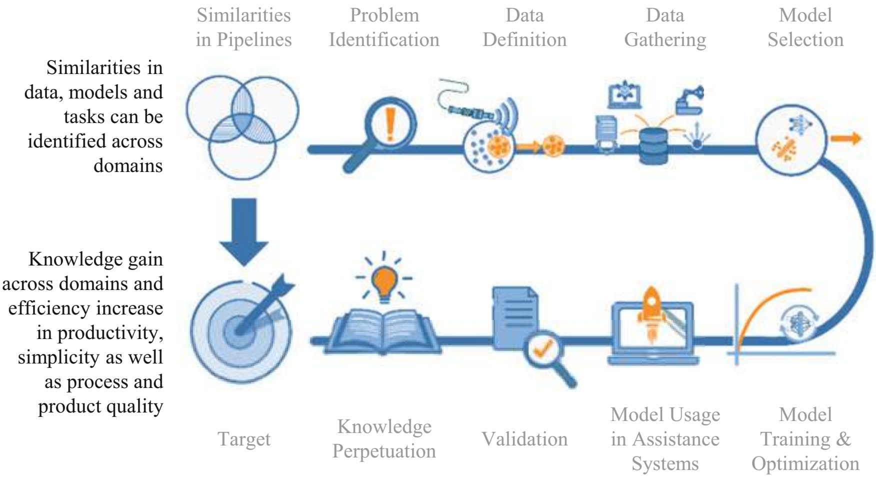


Fig. 12.1 Maturation stages in discontinuous process modeling and efficiency improvement

in different industries with different requirements, full raw process data is often discarded, retained for limited time, reduced to mean values, or isolated in globally inaccessible storage systems with limited capacity. The Internet of Production can only be realized if process data is globally available with sufficient but adequate granularity. A major challenge lies in striking a balance between the required storage for data from one discontinuous production cycle and the ability to retain these cycle data sets over months and years for retrospective analysis. The major challenge is that inquiries about the process may arise much later in time and the scope only becomes clear long after the production process has concluded. Consequently, the granularity of the process data stored cannot be defined beforehand as the objective of later analyses can hardly be predicted. Therefore, initial full retention and global availability of the process data needs to be facilitated to enable in-situ detection of second- and third-order interdependence between sensor and actuator measurements to effectively antedate the retrospectively arising questions relating to the process. By employing such a strategy, the process data can be refined for longer term storage with a reduced overall storage requirement based on the detected correlations and data processing that can be employed right after the sensor values were captured. This strategy relies on three cornerstones: Raw data transfer from the machine to the cloud, data refinement by connecting the full data set of the process including machine and product in an adequate format, and lastly automated analysis of this high granularity data set to detect process interdependencies to facilitate subsequent data reduction where applicable.

When data is defined and readily recorded, the necessary information might need to be extracted for the following model building. Arguably the most important type of data to be considered for data (pre)processing in industrial applications is visual data. In many discontinuous production processes, quality analysis is at least partly done through optical methods (Garcia et al. 2001; Du et al. 2005; Abiodun et al. 2018). Traditionally, this is either realized by simply installing a camera to receive quick information or by measuring the results through more time-consuming methods like microscopy. Both ways have advantages and disadvantages: The information provided by a camera can be obtained easily but is subsequently less detailed than that from microscopes which could lead to missing crucial information in the surface structure. A microscope provides much more detailed information, but it can usually not be used to scan all output products due to the required time or cost. With computational methods, this issue can be addressed to find a compromise between camera and microscope. When the image data is used in quality analysis/prediction, conventionally, various machine learning models are employed for image processing like feature detection (Sankhye and Hu 2020). This can be done with raw image data, but it has been demonstrated that for example in image classification preprocessing of the images leads to far more accurate results (Pal and Sudeep 2016). Similarly, it can be expected that in quality prediction, preprocessing like transforming the images to greyscale, flattening, or using an early edge detection method may improve the accuracy of the models. Both using computational methods for finding the boundary between camera and microscope and using image preprocessing are ways to enhance or enable data used in quality prediction. This can have a bigger impact on machine learning results than modifications of the model itself.

Furthermore, a model should be able to handle a large number of parameters. A great amount of parameters or equations to describe the process, e.g., reduce the computation velocity. This might be harmful considering the subsequent implementation in a control system that aims to be real-time ready. On the other hand, as many input information as possible should be kept for the model design if these effectively contribute to improve the prediction results. In the end, "the reduced order model must characterize the physical system with sufficient fidelity such that performance objectives [. . .] for the controlled physical system can be met by designing control laws with the reduced order model" (Enns 1984). Therefore, especially for the usage of highly dynamic systems such as laser applications, model order reduction is a many times researched field of interest to improve model quality. Laser manufacturing processes are controlled by multi-dimensional process parameters. To model this process numerically, several multi-physics dynamic equations should be solved. However, the high-order parameter dimension and process complexity make it difficult to conduct a solution and establish a data-driven process design. Model reduction is a way to drive a model focusing on specific quality criteria by neglecting unnecessary complexities. These reductions are based on dimensional and scale analysis, empirical model, or numerical model reduction (e.g., Proper Orthogonal Decomposition method (Li et al. 2011)). The model reduction procedure employs a top-to-down approach that begins with complex multi-physic governing equations, and ends to the approximated ordinary differential equations. The main task of model reduction methods is to omit unnecessary complexity and to reduce the computation time of large-scale dynamical systems in a way that the simplified model generates nearly the same input-output response characteristics. They are capable of generating accurate and dense dataset in an acceptable time. These datasets can be used to enrich the sparse experimental data and also, by employing machine learning models, establish data-driven and meta-models.

Besides physical models, data-based models have been gaining a lot of interest in the past years. This may be due to the facilitated development of sensors, data acquisition methods, less costly data storage options, and generally higher availability of highly educated personnel in the domain of data science. The usage of machine learning may be beneficial for the representation of processes whose behavior contains a significant part of hardly explainable or quantifiable phenomena. Examples of discontinuous processes are physical vapor deposition, thermal spraying, or the thermoplastics injection molding process. An efficient model selection, e.g., by hyper-parameter optimization, model training, and strategies regarding how to use the resulting models are unifying steps in the improvement process across different domains and between different discontinuous processes. One common challenge is that, e.g., especially advanced models such as artificial neural networks require a significant amount of training data to prevent underfitting a modeling task.

The generation of manufacturing data of discontinuous processes, however, can be time-consuming and expensive and therefore limited. Lowering this barrier would foster the applicability of machine learning in the manufacturing field in general. To achieve this goal, transfer learning is used as one possible method to demonstrate the potential to reduce the problem of limited training data. In the context of machine learning, "transfer learning"refers to the transfer of knowledge learned from a source domain D_S and a source task T_S to a new task T_T (Weiss et al. 2016). A structured transfer of knowledge is realized through the close relationship of the tasks or domains to each other. The most intuitive approach to transfer learning is induced transfer learning (Woodworth and Thorndike 1901; Pan and Yang 2010; Zhao et al. 2014): Given a source domain D_S and a source task T_S, the inductive transfer learning attempts to improve the learning of the contexts in the target domain D_T with the target task T_T. Here, the source and target tasks differ from each other. The approach assumes that a limited amount of labeled data from D_T is available. This is usually the case for different processes, e.g., when a new process setting is probed. Therefore, transfer learning is one method for data-based process modeling that should be researched further and individually per process while sharing knowledge about approaches and caveats between the settings, especially between different discontinuous processes.

Once all technical challenges are solved, developed models need to be transferred into production as their ultimate legitimation is the support of respective manufacturing processes. All previously considered challenges to easily implement improvements to the process such as significant parameters with necessary information, small models for fast computation, small datasets for advanced data-based models, and more culminate at this stage. During the deployment stage, it is decided if the model or maybe even resulting assistance system is applicable for the users. Concrete difficulties that may arise at this stage for all discontinuous processes might be of three categories: (1) Social: Users and workers might not approve of the resulting measures for the derived model-based improvements. (2) Technical: Sometimes it may be difficult to conclusively prove a value of the derived measures for the company. E.g., a deeper understanding for the workers of the discontinuous process by displaying aggregated information about the process' state might not be directly quantifiable but furthers the workers' domain-specific problem-solving skills. (3) Architectural: Talking about industry 4.0, the resulting improvement involves digital methods significantly. However, companies already use software and usually resent a great variety of different programs and platforms. It is therefore crucial to supply developed models and assistance systems in accordance with the common software integrations in companies to guarantee ergonomic use.

In conclusion, discontinuous processes analogously show similar stages for modeling and when trying to improve process efficiency in its variety of definitions. In particular, problem and data definition, data gathering, data (pre)processing, model order reduction, model design, training and usage, model or assistance system deployment as well as knowledge perpetuation in a final stage which is not extensively considered here are to be named. The following subchapters will give an overview of the stages of research for a variety of discontinuous processes. Significant challenges and possible solutions that may be transferable between processes are highlighted to make the reader acknowledge the previously defined analogies.

12.3 High Granularity Process Data Collection and Assessments to Recognize Second- and Third-Order Process Interdependencies in a HPDC Process

The high-pressure die casting (HPDC) process is a highly automated discontinuous permanent mold-based production technology to fabricate non-ferrous metal castings from aluminum or magnesium base alloys. Typically, a HPDC cell consists of multiple subsystems that are operated by separate PLCs in order to replicate every production cycle as closely as possible. Current generation data acquisition systems are usually limited to only extract averages or scalars from the process at one point in time of the cycle rather than continuously providing data such as die or coolant temperatures to facilitate in cycle assessments. By reducing the amount of acquisitioned measurement data points information about the process is irreversibly lost which prohibits analysis of high-granularity data in retrospect if needed. While some external measurement systems can measure and store this data, typically via SQL databases, currently there is a lack of cloud infrastructure-compatible data pipelines and storage blueprints to facilitate the transfer and retention of high granularity data available via service-oriented architectures such as OPC UA (Mahnke et al. 2009) for downstream analysis. In order to retain the ability to assess the raw and undiluted data a state-of-the-art architecture based on a data lake derived from the Internet of Production infrastructure research activities was deployed to store the process data and enable its assessment (Rudack et al. 2022). In the following an example of the acquisitioned process data extracted from the data lake are presented to illustrate potential use cases and benefits of granular acquisition and long-term data storage. The presented issue to the plunger cooling flow rate. In the HPDC process, the plunger is usually made from a Copper alloy and has to be water-cooled since it is in direct contact with molten Aluminum. A suitable equilibrium temperature range needs to be maintained in order for the plunger to maintain a suitable gap width between itself and the surrounding tool steel, otherwise excessive wear can occur due to metal penetration in the gap or excessive friction at the interface. Effectively, the water coolant supply is the proxy parameter that governs the plunger operating temperature. The top half of Fig. 12.2 shows that during 1 h of HPDC production the flow rate exhibits 6 drops of the flow rate from about 16 l/min to 12 l/min, each lasting around 3 min which corresponds to around 4 production cycles. This puts the plunger-chamber system in a different operating condition. The reason for this phenomenon can be determined with high certainty when a visual

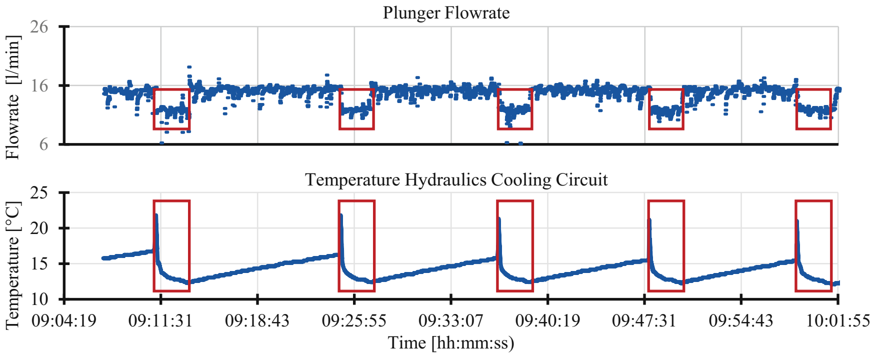


Fig. 12.2 Behavior of the coolant system during 1 h of HPDC operation

synchronization with the water temperature at the heat exchanger of the hydraulics system is made. It is visible that the reduction in plunger coolant flow occurs when the heat exchanger of the hydraulics system is active. The initial temperature peak indicates that the hot water that was static in the heat exchanger is being pushed out by colder water which consequently lowers the temperature until the heat exchanger flow is switched off again by the control system. The plunger temperature and the hydraulics system do not seem like directly interdependent entities from a classical engineering point of view. However, as these measurements show they are indirectly linked via the coolant network of the machine.

These two sensor values serve as an example for a correlation derived from data from the data lake and investigated by a manual data assessment by the domain expert. The next research steps will aim to enable continuous automated assessments for over 300 separate sensor values that are stored in the data lake during HPDC operation as semantically integrated sensor data. We will assess how to derive machine and die-specific process signatures that enable the derivation of the processes' specific digital shadow. By deployment of adequate mathematical methods on the data available through the cloud-native architecture we aim to better understand the second- and third-order consequences of fluctuations in sensor values.

Retention of a full set of process can be beneficial if correlations are initially entirely unknown as outlined above. Generally, vector and scalar data from flow or temperature sensors are not as problematic retain from a storage standpoint as visual data. Surface defects of the casting and die are one defect class where visual data enable an in situ process feedback loop. High-resolution visual data is needed to drive defect detection on both elements: The casting and the die. Imaging systems usually have to find a compromise between slow, high-resolution processes that provide possibly too detailed data for practical usage and fast, low-resolution imaging systems that fail to capture all required details. This can be addressed with computational methods as described in the following.

12.4 Fourier Ptychography-Based Imaging System for Far-Field Microscope

Fourier ptychography (Zheng et al. 2013) is a method based on wave optics to extract the complex electromagnetic field and thus reconstruct images with higher resolution. It is mainly used in microscopy but it can also be applied in systems with higher working distances (Dong et al. 2014). It requires only a simple camera that can be integrated in many processes and employing computational methods to extract more detailed information than what is conventionally achievable.

TOS designed a macroscopic Fourier Ptychography imaging system which is used to take multiple unique images of a distant target object and iteratively reconstruct the original complex electromagnetic field at a much higher resolution, comparable to that of light microscopes. The imaging system is depicted in Fig. 12.3. A Helium-Neon laser is used to create the coherent radiation for illuminating a target. The beam of the laser is expanded with a telescope to emulate a plane wave illumination. It is split into two beams with a beam splitter cube to illuminate the target perpendicularly. The reflected beam then incidents on a conventional camera that can be moved with two linear stages for creating the unique images. The recorded images are saved together with the process parameters and can be used for the reconstruction process at any time.

The acquired images are fed into a data lake. With iterative optimization based on Wirtinger Flow (Chen et al. 2019) this large sum of images is reduced to a high-resolution image that combines all the light field information from each separate image while requiring less memory. No information is lost during the process. This is especially advantageous in processes where a camera cannot be placed in the short distance required by microscopes. In this situation, the reconstruction process acts as a digital twin to the measurement by emulating the experiment in a simulative propagation. An initial guess for the complex field is estimated and the propagation and thus resolution reduction through the optical system is simulated. The goal of the optimization is to minimize the difference between the experimental images and

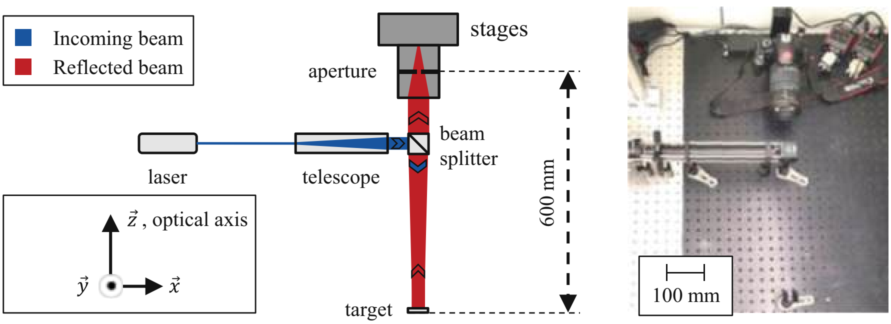


Fig. 12.3 Imaging system

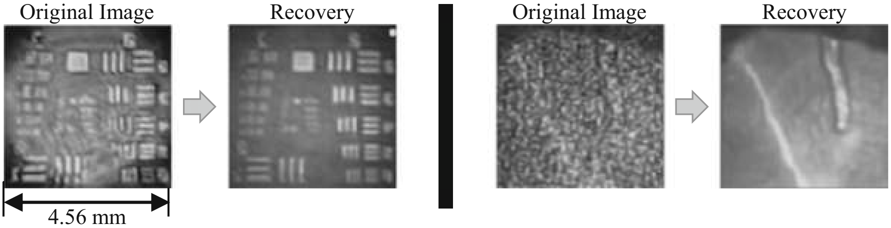


Fig. 12.4 Reconstruction examples

the subsequent low-resolution simulated images which can only be accomplished by finding the underlying high-resolution field.

Example reconstructions of a USAF resolution target and an ivy leaf are depicted in Fig. 12.4. For the resolution target, the achieved resolution with regard to the smallest resolvable structure is increased by roughly 25% but more is expected in future modifications of the setup. Using the reconstructed images for quality prediction based on artificial neural networks was tested in a toy model for high-pressure die casting in a collaboration with Foundry Institute (GI) and the chair of Computer Science 5, RWTH Aachen University (Chakrabarti et al. 2021). This setup may be introduced for all discontinuous processes that need high image resolution without using microscopes. The next research steps are the implementation of a new camera and modifications of the recovery algorithm for faster and more accurate results.

Still, due to high-dimensional and complex physical phenomena, not every process can be fully controlled or optimized experimentally. Also, it is often not possible to do full numerical simulations. A combination of simulations and experiments might be a remedy to this dilemma. One can decrease mathematical complexities by means of model reduction methods, provide solvable equations, and calibrate them by experimental data. Reduced models can simulate the processes in wider ranges of parameters and enrich sparse experimental data. By this potential feature space, more effective feature learning and also feature selection can be established. In addition, by combining the reduced and data-driven models, the applicable boundaries of utilization of reduced models can be specified that can robust the modeling, simultaneously.

12.5 Integrating Reduced Models and ML to Meta-Modeling Laser Manufacturing Processes

Rising capabilities of production procedures require simultaneous improvement of manufacturing planning steps since processes become more complex. One can reach an optimized production plan through process parameter identification, knowledge extraction, and digitization. Experimental studies are limited to sparse data to investigate and control these complex processes. Full numerical simulations

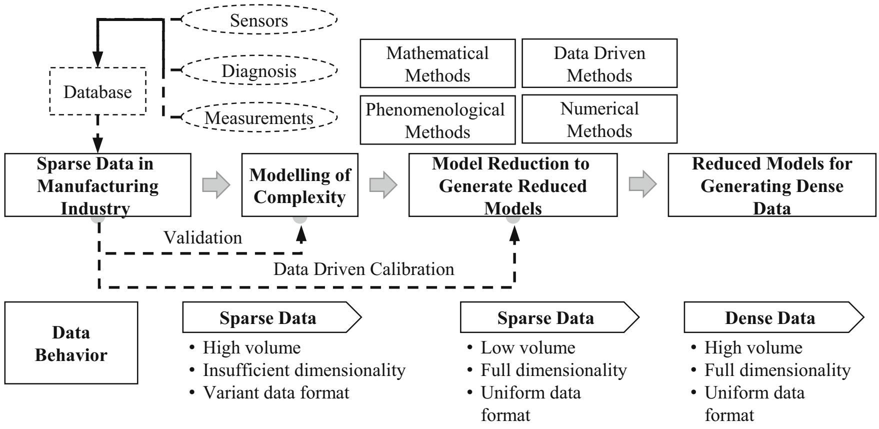


Fig. 12.5 Work-flow to enrich sparse data. (Wang et al. 2017)

are also computationally costly due to the multidimensional complexity of the governing eqs. A practical solution is to enrich experimental data with reduced model simulations called data-driven models. Model reduction techniques which are based on analytic-algebraic, numerical, or empirical reduction approaches are used to decrease the complexities of the governing equations.

Extended work has been done on the subject of laser drilling (Schulz et al. 2013). A reduced model has been proposed (Wang 2021) to simulate the laser drilling process in the melt expulsion regime and consequently to construct a digital shadow of the process. Through the reduced equations, the laser drilling process at the base of the borehole, the melt flow at the hole wall, and finally, the melt exit at the hole entrance are simulated. A sparse experimental dataset is used to validate the reduced model before generating data to enrich the dataset, as depicted in Fig. 12.5 (Wang et al. 2017).

The generated dense data is interpolated to form a meta-model and is a valuable tool in quality prediction, process design, and optimization. In Fig. 12.6, the applicable region of laser drilling is shown, which is estimated based on the maximum height of melt flow in the hole. To this goal, a Support Vector Machine (SVM) classifier is used in meta-modeling, and the applicable beam radii under specific radiation intensity are estimated.

The reduced equations of mass and energy conservation are solved in solid, liquid, and gaseous phases in the melt expulsion regime to analyze the laser drilling process (Wang 2021). This reduced model is established by scaling the equations, applying phenomenological facts, and integral method. However, estimating the shape of the drill hole is still computationally costly requiring a higher level of reduction for the model. Through an empirical model reduction, an intensity-threshold model is developed that estimated the borehole shape asymptotically in the long-pulse laser drilling regime (Hermanns 2018). The approximation of the hole's shape relies on the fact that the material absorbs a specific power intensity

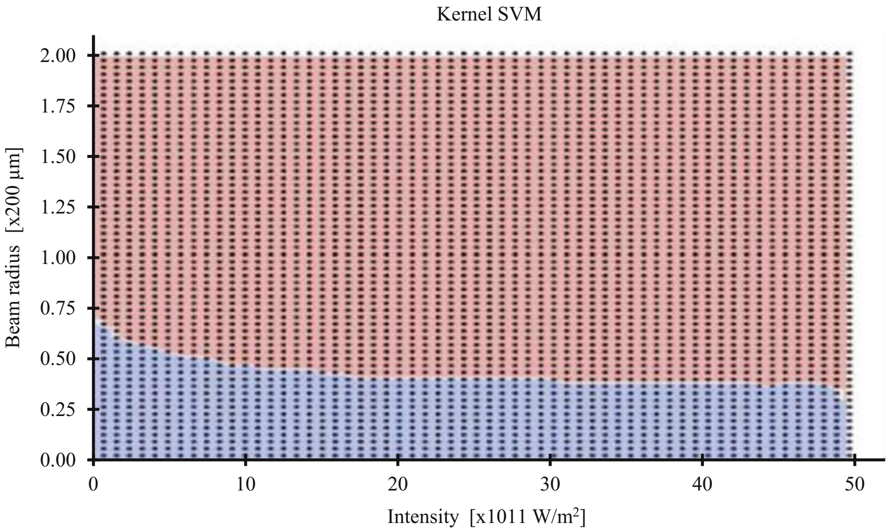


Fig. 12.6 Estimated applicable region by SVM. Red area presents the applicable combination of beam radii and power intensities for laser drilling. (Wang et al. 2017)

after a certain number of pulses and is removed as the absorbed intensity reaches the critical value, named the ablation threshold. Since this asymptotic model is fast and accurate within its applicable region, it could also be used to enrich required data for meta-modeling.

Another application of combining reduced models and ML techniques is inverse solution-finding. This approach was applied to solve a simple trebuchet system through training a deep neural network; it used the Algorithmic Differentiation (AD) technique to embed the trebuchet ODE model in the loss function (Rackauckas et al. 2020). The ANN learns to approximate the inverse solution for a specific hole geometry during training by reproducing the required parameters of the reduced model. The reduced laser drilling model is part of the loss function.

In case the combination of reduced models and sparse or expensive data prove useful for an application, their validity, especially for data-based models, needs to be always critically questioned. Changes in material, machine, surrounding, and many other influencing factors might let the resulting modeling quality to erode. However, working models are the foundation to an automated process optimization, independent of the quality parameters which are chosen to be optimized. Furthermore, complexity of models might not only be measured by the number of input parameters but also the number of connected process steps. A lot of data is, e.g., generated in an Automated Tape Placement (ATP) process including vision-based defect analysis and OPC UA connection to the machine for high granular data. This poses a viable example for the combination of data gathering and enabling steps toward an extensive model for process optimization.

12.6 Vision-Based Error Detection in Automated Tape Placement for Model-Based Process Optimization

As in many highly integrated discontinuous processes, part defects during manufacturing in ATP processes can have a substantial influence on the resulting mechanical or geometrical part properties and are very costly when discovered at a late process stage (Li et al. 2015). Therefore, multiple defect detection systems are being investigated in industry and research (Brasington et al. 2021). Especially economically competitive sensors such as industrial cameras have shown to be feasible (Atkinson et al. 2021) with certain challenges such as low-contrast environments. Automated defect detection with the possibility to adjust the process settings to reduce part defects is therefore the goal of this research.

Multiple defects can occur during AFP, the most common being gaps, overlaps and positional errors, or other processing defects. Firstly, determining tape geometry and defects for one tape are investigated by an in-situ (integrated into production line) inspection of the parts which permits high productivity and throughput. The observed defects include tape length, width, and the cutting edge angle. To detect and quantify these defects, methods of classical image processing are employed. Acquiring process and machine data based on a process model is necessary to feed back process influences onto the laminate quality and finally enable online quality improvements. However, no generic machine component and parameter models currently exist for ATP machines, especially for the integration of quality data. Such a model is required to enable generic correlation of quality data with parameters. Therefore, a machine model on the basis of OPC UA is developed.

The quality inspection system to gather reliable quality data of single tapes consists of a monochrome industrial camera DMK 33GP2000e mounted behind the tape placement head and a manually controllable RGB lighting system mounted inside the machine housing (see Fig. 12.7). The camera is further equipped with a polarization filter mounted to the lens to reduce reflections and increase tape detectability due to the carbon fibers polarizing incoming light during the reflection.

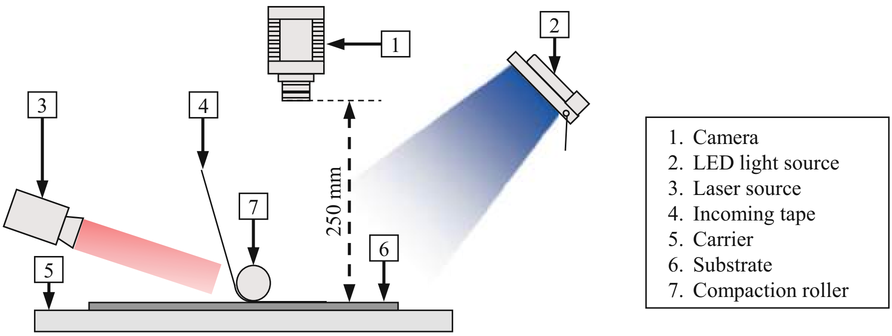


Fig. 12.7 Measurement setup

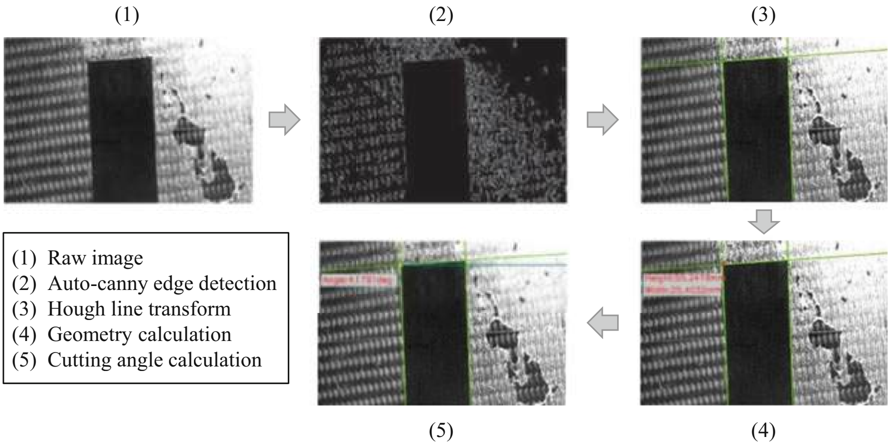


Fig. 12.8 Tape geometry analysis

Different algorithms, namely the Sobel, Prewitt, and Canny operators, are used to detect tape edges, with the Canny Edge Detector outperforming Sobel and Prewitt, since it is able to filter out noise induced by, e.g., the tooling background. However, the detected edges from the Canny edge detection are still quite irregular and not necessarily complete. Therefore, a hough line transform is applied on these edges, creating straight lines in accordance with the tape's geometry.

Figure 12.8 shows the whole analysis process. Using the created tape contour, the tape's geometrical features as well as the cutting angle can be accurately extracted from the images with knowledge about the pixel/mm factor and the intersection between the vertical and horizontal hough lines. The latter can give an indication about cutting unit and knife wear, i.e., increasing cutting angle points to dull blades and therefore indicates upcoming maintenance.

Subsequently, a model using OPC UA to describe the tape placement system by combining machine settings, process, and quality parameters is developed. The model is semantically categorized into different functional groups. One group represents conveying the tooling through the machine. The next group is responsible for orienting the fiber angle. The last group aggregates the functionality to place the tapes, including the required motion for unrolling the tape from the spool, as well as the tape placement head components. The tape placement head is again encapsulating multiple functional components, e.g., cutting unit, feeding unit, heating unit, and pressure application unit.

This model-based approach gives a clear overview of the process parameters, decoupled from the individual machine components. Next, context-aware analysis of process parameters and their interdependencies can be realized, revealing influences of the process as well as the machine system on laminate variations and defects. These interdependencies then can be used to optimize part quality prior to manufacturing as well as online from part to part. The modeling for the ATP process displays the challenges for integrated discontinuous processes and may later be taken as a blueprint for other processes for the combination of process information. Further example for the design and training of data-driven models can be found in the area of surface engineering, e.g., for physical vapor deposition (PVD) and thermal spraying (TS) processes.

12.7 Understanding Coating Processes Based on ML-Models

Surface engineering enables the separated optimization of the volume and surface properties of materials. In manufacturing technology, this is crucial for increasing performance or lifetime. The main motivation for employing coating technologies such as PVD and TS are resource savings, environmental protection, and increasing demands on safety and efficiency attributes. PVD and TS are associated with numerous process parameters and represent two important discontinuous coating technologies.

TS is a versatile coating technology regarding the wide variety of feedstock materials, which can be introduced into the high-temperature free jet to deposit a coating. The resultant molten or semi-molten particles are accelerated toward a prepared substrate and build a coating by successive impingement. TS offers a wide range of functional features including wear, oxidation and corrosion resistance as well as thermal insulation. Therefore, many industrial sectors benefit from the special characteristics of this coating technology. In the PVD process, a solid target material is transferred into the gaseous phase in a vacuum chamber. Within the gas or plasma phase, interactions take place between the ionized and excited species. Inert gases, such as argon or krypton, are used as process gases or reactive gases, such as nitrogen and oxygen, are added to the gas phase for active participation within the coating formation. The species in the plasma are transported toward the substrate at which the coating grows. Knowledge of particle properties in the TS process or the plasma in the PVD process is necessary for adequate coating development. The understanding of the coating processes and the influence and selection of process parameters can be supported by Machine Learning (ML).

The numerous parameters and their nonlinear interactions influencing TS can lead to a time-consuming and costly endeavor to control and optimize the processes. Simulation and modeling methodologies such as Computational Fluid Dynamics (CFD) are frequently used to represent the associated complicated physical processes. Although CFD has a strong potential for understanding the sub-processes of TS, the balance between model accuracy and computational cost has always been a concern. The modeling of the particle free-jet in a multi-arc plasma spraying process, which is the subject of this work, necessitates a high computing cost without losing model accuracy. The use of ML methods to construct a Digital Shadow is a promising solution for replacing computationally intensive CFD simulations.

Therefore, a Digital Shadow for the plasma spraying process was developed that can predict the average particle properties depending on different sets of process parameters using CFD simulations and Support Vector Machine (SVM) models.

The simulation data sets were obtained in form of a 45-sample Latin Hypercube Sampling (LHS) test plan from a former numerical model for the plasma spraying process of a three-cathode plasma generator (Bobzin and Öte 2016). The simulations were also validated experimentally by in-flight particle diagnostic measurements (Bobzin et al. 2016). The feedstock material for the simulations was alumina. The parameters for the LHS, respectively, the inputs of the ML-models are given in Table 12.1.

Two single-output SVM models for the in-flight particle temperatures T_p [K] and velocities v_p [m/s] were developed. Gaussian kernels with different kernel scales were probed as SVM-hyperparameters for the best prediction accuracy. From each of the 45 simulations, 75% of the data were used as training data and the remaining 25% as test data. Figure 12.9 shows exemplarily the results of the mean particle velocities at the spray distance of $y = 100$ mm for particle diagnostic experiments, simulations and SVM-models for different sets of process parameters. Although the prediction accuracy is slightly lower for some unconventional process parameters outside the training data range, the developed metamodels have high accuracy in predicting particle properties with average $R^2 \approx 0.92$ for v_p and T_p. Figure 12.9 shows also good agreement of the experimental measurements with the analytical models.

Table 12.1 Parameter setup for the LHS method

Parameter [unit]	Interval
Primary gas flow [SLPM]	40–60
Electric current [A]	400–540
Carrier gas flow [SLPM]	3.5–7.0
Powder feed rate [g/min]	10–30
Particle size distribution [µm]	−35 + 15; −55 + 35; −75 + 55
Stand-off distance [mm]	100–180

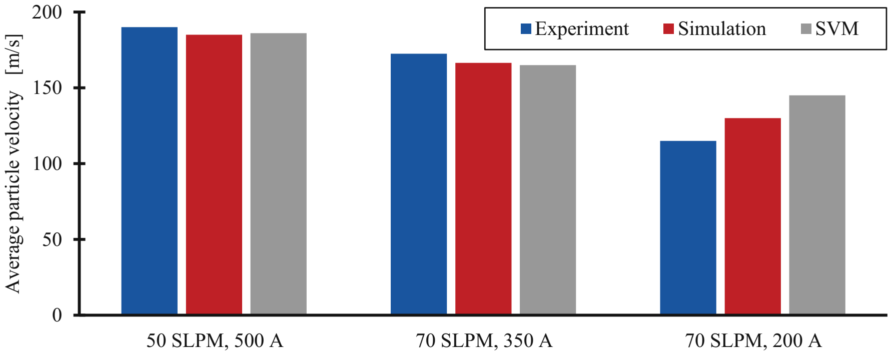
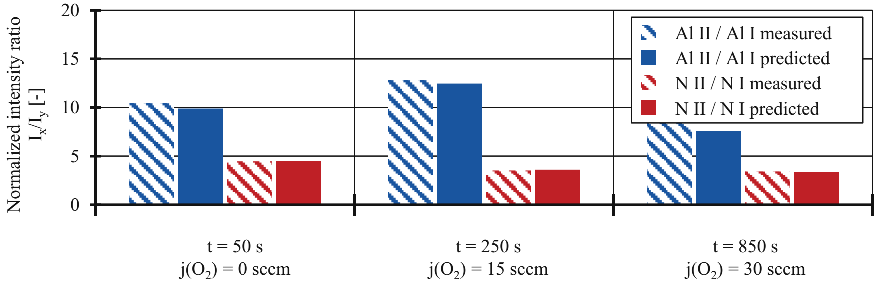


Fig. 12.9 Exemplary results of mean particle velocities for experiment, simulation, and SVM for different sets of process parameters

The average computational time of one plasma jet simulation in combination of the corresponding plasma generator simulation is about 3 h, in comparison to roughly 4 s prediction time of the metamodels. The developed ML-models drastically reduce the computational cost while preserving high prediction accuracy. The conducted work serves as basis for the creation of the complementary concept of Digital Twin for plasma spraying.

In PVD, the process parameters are usually selected by the operator based on experience and analysis results. Nonlinear interactions and influences between individual process parameters are difficult to determine by algebraic methods and require improvement of the process monitoring to reduce the time of coating development. During the coating process, different interactions of gas and metal species take place in the gas and plasma phase. Among other things, the ionized and excited state and the energies of the species are decisive for the resulting formation and the properties of the coatings. Knowledge of these processes is important for the understanding of the PVD coating process and the selection of process parameters during coating development. Methods of plasma diagnostics offer various possibilities for the investigation of the plasma processes. However, the installation of special diagnostics is necessary, time-consuming, and cost-intensive. Machine learning methods can be used to support coating development. They can be applied to predict and identify high ionization and excitation states and to assist the operator in time and cost-effective selection of process parameters.

To achieve high prediction accuracies, a large database is required for modeling and training of machine learning models, such as artificial neural networks. In this study, measured process and plasma data were used to develop a neural network to support the understanding of the phenomena in the PVD process. For dynamic time-dependent prediction, a recurrent neural network (RNN) is suitable (Abiodun et al. 2018). The model was trained with the process and plasma data of 41 data sets for the deposition of CrAlON coatings using the Levenberg-Marquardt algorithm. 70% of the dataset served for training, 15% for validation, and 15% for testing. All coating processes were performed by hybrid direct current magnetron sputtering/high power pulsed magnetron sputtering (dcMS/HPPMS) using an industrial coating unit CC800/9 HPPMS, CemeCon AG, Würselen, Germany. Within the processes, the cathode powers P_{dcMS} and P_{HPPMS} and gas flows $j(N_2)$ and $j(O_2)$ were varied over the deposition time. Substrate bias voltage U_B and argon gas flow j(Ar) were kept constant. Resolved over the deposition time, the intensities of the excited "I" and singly ionized "II" species in the plasma were recorded by optical emission spectroscopy. The intensities were measured at six positions distributed in the chamber, each at the substrate position opposite of a cathode. The II/I ratios were calculated for the species in the plasma. For each ratio of the species in the plasma, the optimized number of hidden layers for the model was determined. As result, a range between five and 20 hidden layers indicated that separate models should be trained for the different species to achieve the highest possible accuracy. As an example, for Al II/Al I an amount of 20 hidden layers was identified as suitable, for N II/N I ten hidden layers were chosen. The RNNs were trained and used to predict the ion intensities at different timestamps of a new data set in which the oxygen gas



Constant Parameters	P_{HPPMS} [kW]	P_{dcMS} [kW]	j(Ar) [sccm]	$j(N_2)$ [sccm]	U_B [V]
	2.5	1.5	200	100	-100

Fig. 12.10 Intensity ratios measured and predicted using RNN at different time steps and oxygen gas flows for Al II/Al I (blue) and N II/N I (red)

flow was varied. After the prediction the same process was performed and measured. Figure 12.10 shows the predicted and subsequently measured intensity ratios N II/N I (red) and Al II/Al I (blue) at different timestamps of the exemplary process. At the timestamps t = 50 s, t = 250 s and t = 850 s different gas flows were present. The predicted results showed an equal range of values, equal tendencies, and a good agreement with the measured values over the process time within the data set. With increasing oxygen gas flow and process time, the normalized intensity ratio N II/N I decreased. A decrease of the normalized intensity ratio Al II/Al I was also seen from t = 250 s with $j(O_2)$ = 15 sccm to t = 850 s with $j(O_2)$ = 30 sccm. This indicates an increasing poisoning state of the target used. To evaluate the prediction accuracy, the Mean Square Error MSE was calculated, which is close to zero at a high accuracy. The prediction showed for Al II/Al I a MSE = 0.361 and for N II/N I a MSE = 0.031. The RNN provides insight into the behavior of the species in the plasma and supports the operator during parameter selection.

The diverse data sets of coating technologies offer great potential to gain new insights into these complicated processes and to develop and improve the processes in a fast manner. ML methods may help to obtain the added value of this data. The developed models for TS and PVD can be used to advance Industry 4.0 in the field of surface technology and beyond in general for discontinuous processes. Furthermore, industrial transfer learning can be implemented to use the collected data source in this study for other process variants or different production domains. As a result, new accurate and data-efficient models can be created or the generalization capability of the used models can be improved. A currently active research for the transfer of knowledge between machine learning models describing discontinuous processes can be seen for injection molding.

12.8 Transfer Learning in Injection Molding for Process Model Training

In injection molding, one of the most complex tasks for shop floor personnel is the definition of suitable machine parameters for an unknown process. Machine learning models have proven to be applicable to be used as surrogate model for the real process to perform process optimization. A main disadvantage is the requirement of extensive process data for model training. Transfer learning (TL) is used together with simulation data here to investigate if the necessary data for the model training can be reduced to ultimately find suitable setting parameters. Based on different simulation datasets with varying materials and geometries, TL experiments have been conducted (Lockner and Hopmann 2021; Lockner et al. 2022). In both works, induced TL (Pan and Yang 2010) by parameter-based transfer was implemented: Artificial neural networks (ANN) have been pretrained with datasets of injection molding processes, each sampled in a 77-point central composite design of experiments (DoE), and then retrained with limited data from a target process (one-one-transfer, OOT). The values of the independent variables injection volume flow, cooling time, packing pressure, packing pressure time, melt, and mold temperature have been varied, and the resulting part weight was observed as a quality parameter.

TL can significantly improve the generalization capability of an ANN if only a few process samples of the target process are available for training (comp. Figure 12.11). On average, this lowers the necessary experimental data amount to find suitable machine parameter settings for an unknown process. Consequently, this accelerates the setup process for manufacturing companies. However, depending on the transferred parameters, the model's generalization capability may vary significantly which may impair the prediction accuracy. The geometry of the

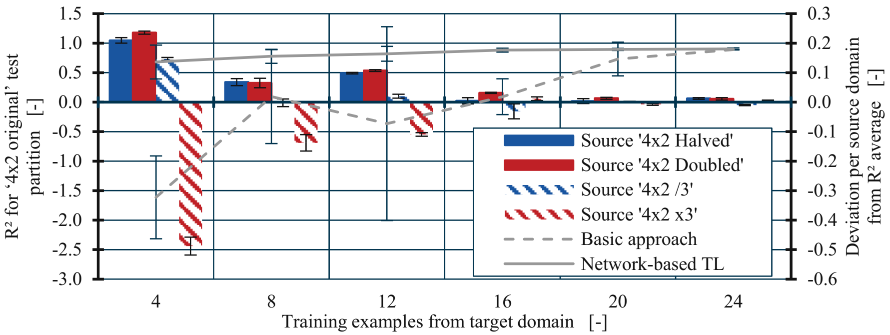


Fig. 12.11 Results of transfer learning experiments (left axis) and model generalization capability for supplied source dataset (right axis) according to. (Lockner and Hopmann 2021)

produced part and its belonging process model can have a significant impact: For the depicted results, 60 different geometries for toy brick were sampled, e.g., "4 × 2" for 2 rows of 4 studs and "Doubled" for doubled shoulder height of the toy brick relatively to the "Original" geometry, which was used as target domain. For source datasets "4 × 2 Doubled" and "4 × 2 Halved" the ANN achieve the best result for the data availability between 4 and 12 target process samples. However, the source domain "4 × 2 x3" should not be used: The inferior TL results may stem from the geometrical dissimilarities between "4 × 2 x3" and "4 × 2 Original": All dimensions, including the wall thickness, are tripled for "4 × 2 x3" in comparison to "4 × 2 Original" which strongly influences the filling, packing, and cooling phase of the process (Johannaber and Michaeli 2004). Therefore, it is necessary to identify a priori which source model is most suitable to be used as a parameter base for the target process in a transfer learning approach.

For that, a high-level modeling approach has been designed, using the transfer learning results for 12 target process samples (compare Fig. 12.11) of the bespoken experiments in (Lockner and Hopmann 2021) as training data. The transfer learning success measured by R^2 served as a quality parameter. Twenty-five geometrical parameters describing the parts of the injection molding processes and whose values are known before production have been identified. Among them are, e.g., the part length, width and height, maximal wall thickness, flow path length, volume, and surface of the part. Each of the 60 parts has been valued by these parameters. As the training data stems from the OOT transfer learning results, the absolute differences in each geometrical dimension were calculated and served as input data for the modeling.

Different model strategies were evaluated in a nested six-fold hyperparameter optimization: Lasso Regression, Random Forest Regression, Polynomial Regression, Support Vector Regression, AdaBoost, and GradientBoost (Freund and Schapire 1997; Breiman 2001; Hastie et al. 2008; Pardoe and Stone 2010). AdaBoost with Support Vector Regression as base model achieved the lowest mean squared error with 0.0032 and a standard deviation of 0.0055 and was therefore chosen as modeling strategy for the given task. To determine the generalization capability on unseen data, a leave-one-out cross-validation (LOOCV) has been performed with the AdaBoost algorithm, using Support Vector Regression as base model. AdaBoost yielded an average model quality of 0.805 for R^2. The predictions and true values are depicted in Fig. 12.12. One anomaly in the training dataset resulted in a great error, compared to the rest of the predictions. In total, suitable OOT source processes for transfer learning could be predicted by the presented approach. Being able to determine good source models for induced transfer learning may effectively contribute to the reuse of collected manufacturing process data within the Internet of Production and beyond to reduce the costs for generating training data.

Optimized models can then, e.g., be used together with evolutionary algorithms to determine suitable machine setting parameters (Tsai and Luo 2014; Sedighi et al. 2017; Cao et al. 2020). Further validation needs to be done with experimental datasets. Once validated, models need to be transferred into industrial use for a

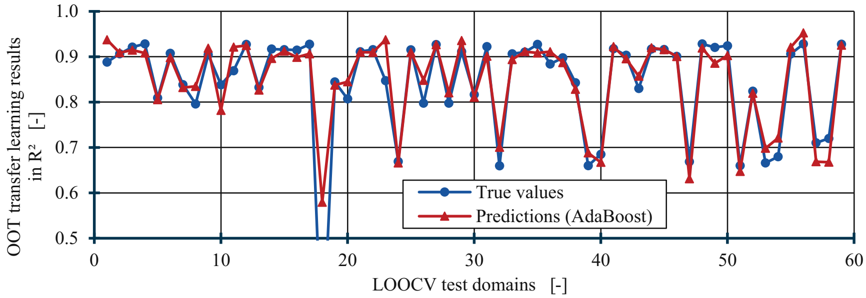


Fig. 12.12 LOOCV results for 59 OOT transfer learning results and AdaBoost modeling

competitive advantage for applying companies. Apt examples are, e.g., assistance systems or modules for simulation software that extend state-of-the-art commercially available software either by raising accuracy or unlocking different fields of applications. Other examples are actively being developed for the open-die forging and laser cutting process.

12.9 Assistance System for Open-Die Forging Using Fast Models

For the specific adjustment of material properties, during forging a certain temperature window must be maintained and a sufficiently large deformation must be uniformly introduced into the entire workpiece. Therefore, an assistance system was developed at the IBF, which measures the workpiece's geometry, calculates the component properties, and adjusts the pass-schedule based on these calculations.

Over the last decades, several approaches for assistance systems for open-die forging have been developed. *Grisse* (Grisse et al. 1997) and *Heischeid* (Heischeid et al. 2000) presented the software "Forge to Limit," which can be used to design a process time-optimized pass-schedule. The online capability was demonstrated via the integration of this pass-schedule calculation with a manipulator control. The commercially available system "LaCam" (Kirchhoff et al. 2003; Kirchhoff 2007) from "Minteq Ferrotron Division" measures the current geometry with several lasers and calculates the core consolidation for each stroke. The press operator is given the position of the next stroke with the aim of achieving a homogeneous core consolidation.

In the system shown in Fig. 12.13, the current geometry is determined with the aid of the current position of the manipulator gripper and cameras, then transferred to a program for calculating the workpiece properties. After comparing actual and target geometry, the program calculates a new pass-schedule, so that process deviations can be corrected continuing the process. The new pass-schedule is transferred to an SQL database developed by "GLAMA Maschinenbau GmbH"

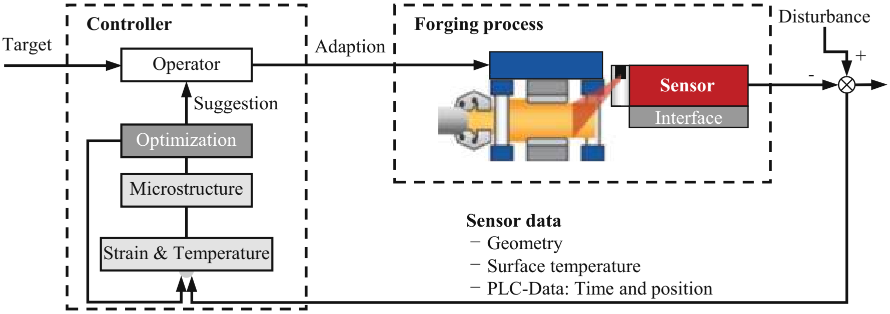


Fig. 12.13 Structure of the assistance system for open-die forging

on the manipulator's control computer, which contains the manipulator positions for each stroke of the remaining forging and passes this information to the press operator via a GUI. Therefore, this system architecture thus enables automatic adjustment of the pass-schedule during forging.

The basis of the assistance system is the knowledge of the current geometry and the current position of the part relative to the open-die forging press. The position of the gripped end of the workpiece corresponds to the position of the manipulator gripper. This is calculated using the inverse kinematics from the measured angles of rotation and cylinder strokes of the 6 axes of the manipulator. However, the position of the free end of the workpiece cannot be obtained from machine data. For this purpose, two HD thermographic cameras by "InfraTec" were positioned laterally and frontally to the forging dies. Edge detection can be used to determine the position of the free end of the part, which, together with the position of the gripped end, provides a very accurate estimate of the touchdown point of the press relative to the forged part. In addition to the workpiece's position in space, its current geometry is also determined from the camera data. Following the calculation, the detected geometry is drawn in green dashed in the live image, so that the quality of the geometry detection can be checked at any time in the process. Despite the large amount of computation required for the live display, a calculation run in MATLAB takes only 50 ms, so that the measurement frequency is 20 Hz.

The geometry data is passed to models for temperature (Rosenstock et al. 2014), deformation (Recker et al. 2011), and grain size (Karhausen and Kopp 1992) with short calculation times, so that these properties can be calculated and displayed live during the process (Rosenstock et al. 2013). The process can now be optimized on the basis of these results, in this case, using the MATLAB-based algorithm "pattern search." Figure 12.14, left, shows the equivalent strain distribution after optimization by the stroke wizard and for a comparative process with bite ratio 0.5 and 50% bite shift after every second pass. The optimization adjusts the bite ratio between 0.45 and 0.55 for each stroke to enable a homogeneous distribution of the equivalent strain without pronounced minima and without fundamentally changing the process parameters. Overall, the minimum equivalent strain can thus

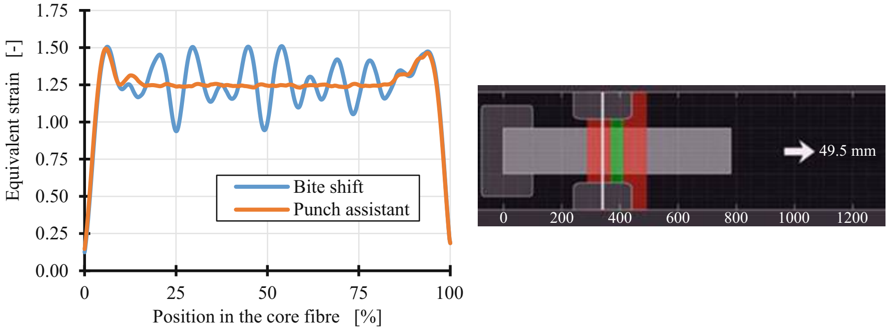


Fig. 12.14 Equivalent strain distribution for a normal process and with punch assistant (left) and GUI (right)

be increased from 0.95 to 1.27 while maintaining the same process time. This optimized process planning is transferred to the press operator via a GUI, see Fig. 12.14, right. There, the current position of the workpiece relative to the dies and the distance to the position of the next stroke are displayed to the press operator to evaluate the program's suggestion and, if judged necessary, implement it.

12.10 Development of a Predictive Model for the Burr Formation During Laser Fusion Cutting of Metals

Most laser-based manufacturing processes are characterized by a significant number of processing parameters that directly or indirectly influence the quality of the final product. To help better understand physical sub-processes, optimize process parameters for a specific task or correctly predict product quality, process simulations often must include phase changes, multi-physical interactions as well as largely varying space and time magnitudes (Niessen 2006). Here we present the development of a numerical model for laser cutting, specifically for predicting the formation of burr, a major quality issue for the process. The approach builds on existing software to construct a useful digital model, that can be integrated in meta-modeling methods and used to derive and validate digital shadows of the process.

Laser cutting utilizes multi-kilowatt high-brilliance lasers to cut sheet metal ranging in thickness from 50 μm to over 100 mm. In the interaction zone between laser and metal, a continuous melt flow is produced, driven by a high-pressure co-axial gas jet (e.g., N_2). A cut kerf is formed when the laser beam and the gas jet are moved relative to the work piece (see Fig. 12.15). The melt flows along the cutting front and the cut flanks toward the bottom of the sheet where it is expelled. On the bottom edge of the cut flanks, adhesive capillary forces act against the separation of the melt and can lead to a melt attachment and recrystallization. A residue-free cut is produced when the kinetic energy of the melt flow is sufficiently greater than the adhesion energy on the bottom of the flank. Otherwise, even the adhesion of a small

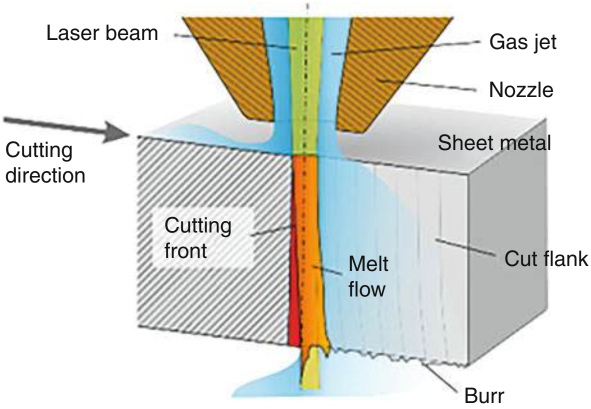


Fig. 12.15 Laser cutting overview, cross-section through gas nozzle and cut kerf

portion of the melt can act as a seed for the formation of long burrs (Stoyanov et al. 2020). Thus, the relation of kinetic and adhesion energies along the separation line, expressed by the Weber number of the flow, can be used to describe the tendency of the process to produce a burr (Schulz et al. 1998).

Apart from the material parameters, the Weber number depends on only two process variables: velocity and depth of the melt flow. To determine their values, a three-step approach proved to be efficient. In the first step, CALCut is used, a laser cutting simulation and process optimization software (Petring 1995). The software is based on a 3D steady-state model of the process. In a self-contained formulation, the model links the sub-processes of laser beam absorption, heat conduction, phase transformations as well as momentum transfer from the gas jet. However, the spatial domain of CALCut includes only the semi-cylindrical cutting front and does not consider melt flow along the cut flank or burr formation. Here, it is used to mainly calculate the geometry of the cutting front and the melt surface temperature as a function of the processing parameters. In the second step, a numerical model is created in the Ansys Fluent simulation environment to extend the numerical domain to include the cut flank and the gas nozzle geometry. We use a two-phase volume-of-fluid model in a pseudo-transient time formulation to simulate the distribution of the supersonic compressible gas flow and its interaction with the melt in the kerf. The melt flows into the simulation domain through an inlet with the shape and temperature as calculated in CALCut. In the third step, the numerical model was experimentally calibrated. The pressure gradients of the gas jet were visualized using a schlieren optical system. This allowed, for instance, a more accurate adjustment of the turbulence and viscosity sub-models as well as the near-wall treatment. The distribution and velocity of the simulated melt flow were experimentally tested using an in-situ high-speed videography. As shown in Fig. 12.16, the simulation results already show good agreement with experimental investigations.

The presented workflow of gathering simulative and experimental data is currently used to produce a multidimensional meta-model of the flow regime depen-

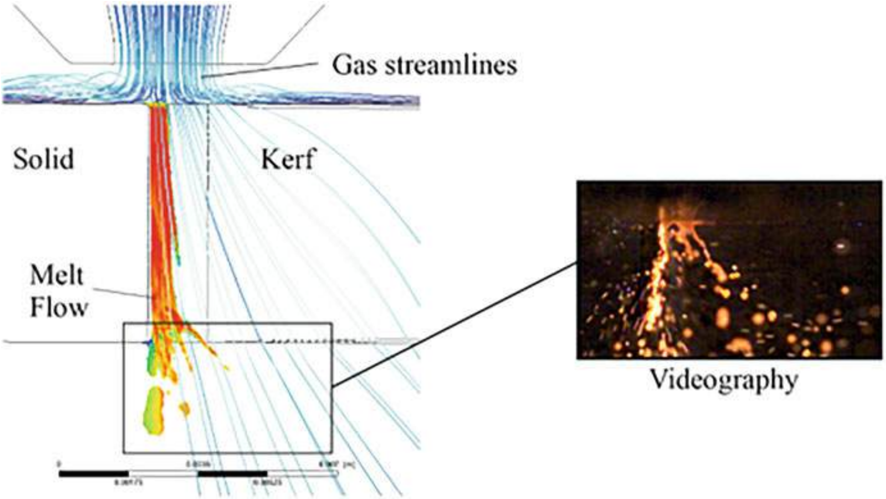


Fig. 12.16 Simulated (left) and experimentally acquired (right) distribution of the melt outflow

dence to the process parameter. The collected data set will be utilized to create a data-driven reduced model and subsequently a digital shadow of the process, according to the model described in Sect. 12.5.

Even though assistance systems might be ready to use, the manyfold of solutions from single silos will add up complexity that could confuse the end-users. Thus, a variety of different systems and models may ultimately be agglomerated into a central register or platform. The digital shadow for the previously described service is intended to be designed in such a way that it can be easily integrated into an IOP microservice software infrastructure. On the example of manufacturing process implementing laser technology and based on some previously described research, such a microservice infrastructure is described in the following subchapter.

12.11 Individualized Production by the Use of Microservices: A Holistic Approach

Many digital shadows for discontinuous processes ranging from simulation over machine learning models as well as data-driven methods were introduced. From a software engineering perspective, these digital shadows can be seen as services or microservices in a discontinuous production process which can be consumed on demand in order to fulfill specific tasks. To this date, the lack of integration of these services has been holding back the possible agility of discontinuous production processes. We propose a holistic approach which exemplarily shows the opportunities of centralized services for laser technology by a software architecture design which allows the quick integration and monitoring of these services.

A main advantage of laser-based manufacturing is that light can be influenced directly and very precisely. In the case of scanner-based manufacturing systems like Ultra Short Pulse Ablation, Laser Powder Bed Fusion, or Laser Battery Welding this advantage becomes apparent since a rise in geometry complexity does not necessarily yield a rise in production costs (Merkt et al. 2012). This "complexity for free" effect could be enhanced further by the integration of pre-validation, simulation, and quality assurance algorithms. The described methods in Sects. 12.4, 12.5 and 12.10 are respective examples for these types of algorithms which could potentially be integrated as support services into a laser production process. Transferred to an exemplary digital laser-based manufacturing system, the process would consist of the following steps.

Before running a production process, the usage of one or multiple services which queries previously attained experiments done with specialized monitoring equipment and sensors can be used to define a possible process parameter window for the production setting. The window greatly reduces the possible number of process parameters combination for a defined quality. A typical example for such a service is explained in ▶ Chap. 10, "Internet of Production: Challenges, Potentials, and Benefits for Production Processes due to Novel Methods in Digitalization" where schlieren pictures could be used and pre-analyzed to define a burst rate for USP Lasers or a gas pressure for laser cutting. Afterward, this process window can be reduced to a single parameter set for the manufacturing machine by using simulation services. Here, the process-specific moving path of the laser would be considered as well, leading to more accurate process parameters. Again ▶ Chap. 5, "Actionable Artificial Intelligence for the Future of Production" contains a detailed description of such a service. The generated process parameters are sent to the machine which is implemented as microservice reachable inside a manufacturing network and the production of the part starts. After the process, an image for quality assurance is generated by calling the quality evaluation service, which connects again to the actuators and sensors of the machine and evaluates and saves the image for further inspection. One of the inspection systems that may be used is described in ▶ Chap. 4, "A Digital Shadow Reference Model for~Worldwide Production Labs".

To combine the single services to a joint manufacturing system, a logical job controller has to be introduced which holds the logic of the manufacturing process and organizes data flow. This chapter holds an example architectural overview of such an approach (Fig. 12.17). The job controller gathers and adapts information delivered by support services (simulation, path generation, process parameter generator) and sends them to the sensor actuator system.

Service-oriented architectures and microservices have been a vital and successful architecture pattern in recent years which allowed large web corporations like Netflix or Google to build and especially run scalable and flexible software systems (Dragoni et al. 2017). This style of architecture is used by industry standards like OPC UA which provide the underlying standardized interfaces for communication, like request/reply communication, service discovery, and some communication security (Jammes et al. 2014). However, these standards do not provide proficient Know-How on the whole service life cycle like deployment, scheduling, updating,

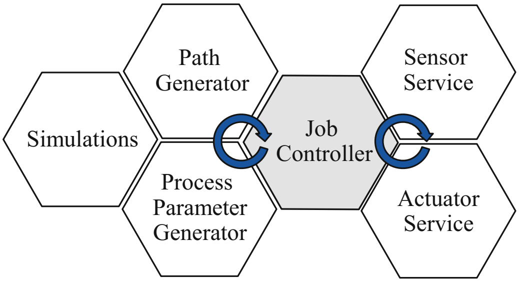


Fig. 12.17 A holistic approach for flexible laser control

access management, etc., which needs to be solved to build a truly adaptable manufacturing machine.

In the Internet of Production, the microservice architecture, dominated by the web industry standards Kubernetes and Docker (Carter et al. 2019) has been evaluated in order to schedule, deploy, update, and monitor manufacturing services. In this architecture, the actual process logic is shifted inside a jobcontroller remotely controlling machines from a data center. In case of resource shortage, new machining edge nodes are added flexibly to the system. One of the main aims of this lab setup is to evaluate the use of Kubernetes and other open source technologies for the use as a shop floor management system. In this scenario, multiple USP Machining Edge Nodes have been connected to a datacenter.

The usage of Kubernetes as a control plane for the USP Machining Edge Nodes and Datacenter Nodes allowed a transparent scheduling and supervision of hardware and support service with the same underlying infrastructure reducing the cognitive load when working with these systems in parallel. However, introducing these architectural patterns through an orchestration system made the system more complex but reduced the effort of adding additional components to the system. Due to the scalability effects, a manufacturing cluster like this could easily be deployed in a manufacturing plant. It poses a suitable foundation for a manufacturing control plane for multiple hundreds of single manufacturing system services. While the initial cost of the infrastructure set up and operation is raised through the use of microservices, the monetary gains from the centralized control plane when building larger system compensate these initial costs (Esposito et al. 2016).

12.12 Conclusion

Efficiency and productivity increase is most relevant in many manufacturing environments. Changing customer demands and tendencies toward smaller tolerances and higher process transparency force companies to adapt their own production. A deeper understanding of the specific processes and therefore the possibility to succeed in a continuous improvement process may be significantly influenced by the change introduced by Industry 4.0: Increased data availability due to new sensors, efficient data transfer protocols or easy cloud-based data storage guides much research interest toward the integration and pairing of digital methods with traditional manufacturing processes to achieve the mentioned objectives.

For a variety of discontinuous processes, a common procedure toward achieving higher production efficiency and productivity has been described. Shared challenges in the stages like problem definition, parameter and data definition and gathering, model design and order reduction, model training and usage as well as deployment of mature assistance systems were identified. Based on different manufacturing technologies, possible solutions and their general applicability for similar process technologies are shown. Especially the application of machine learning methods for an accurate representation of complex manufacturing processes across different domains appears to be a promising approach toward productivity increase. Once mature, bespoken models and approaches need to be transferred into production.

While successful use cases and process-specific solutions, e.g., for data acquisition and processing or model order reduction, for process modeling can be found across manufacturing technologies, an abstract, holistic procedure for process optimization for discontinuous processes as well as a common data structure has not yet been described. Future research in the Internet of Production will focus on the transferability of the previously described solutions for easy integrability in other discontinuous process technology and therefore increase future innovation potential.

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Decision Support for the Optimization of Continuous Processes using Digital Shadows

13

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Abstract

Decision support systems can provide real-time process information and correlations, which in turn assists process experts in making decisions and thus further increase productivity. This also applies to well-established and already highly automated processes in continuous production employed in various industrial sectors. Continuous production refers to processes in which the produced material, either fluid or solid form, is continuously in motion and processed. As a result, the process can usually not be stopped. It is only possible to influence the running process. However, the highly nonlinear interactions between process parameters and product quality are not always known in their entirety which led to inferior product quality in terms of mechanical properties and surface quality. This requires accurate representations of the processes and the products in real-time, so-called digital shadows.

Therefore, this contribution shows the necessary steps to provide a digital shadow based on numerical, physical models and process data and to couple the digital shadow with data analysis and machine learning to enable automatic decision support. This is exemplified at various stages throughout two different process chains with continuous processes: first, by using a thermoplastic production process called profile extrusion, and second, on the example of a metal processing process chain, from which three processes are described in more detail, namely, hot rolling, tempering, and fine blanking. Finally, the presented approaches and results are summarized.

Keywords

Decision support · Process optimization · Digital shadow

13.1 Introduction

This contribution describes the prerequisites for the development of decision support in real time for further process optimization of continuous processes . In continuous processes, the material, either fluid or solid form, is continuously in motion and processed. This production type has been applied for nearly a century in almost all industrial sectors of production, for example, in the plastic or metal processing industry. This long history has led to well-established and often highly automated processes.

However, the physical interactions between process parameters and material behavior that determine product quality are still not well understood or even unknown in detail, especially in complex manufacturing contexts, as the interactions are highly nonlinear. For instance, the start-up and shutdown phase of processes or material property fluctuations can still lead to inferior product quality in terms of mechanical properties and surface quality. Therefore, the challenge is to predict and control final product quality within each production step and along process chains. Current approaches are based on heuristics, expert knowledge, or long trials which are usually time-consuming and costly and often do not lead to generalizable insights.

Therefore, concepts and methods presented in the context of the Internet of Production (IoP) (Pennekamp et al. 2019) such as digital shadows are combined with different algorithms to enable decision support systems to increase the productivity. Digital shadows are situation-specific real-time representations of the material behavior and the process. These digital shadows consist of simulation results from (reduced) numerical and physical models as well as of aggregated data and process knowledge. Combined with algorithms for data processing and analysis, such digital shadows can provide automatically analyzed correlations between process parameters, material behavior, and final product quality. These correlations, together with the numerical and physical models, can then be used to provide real-time suggestions for optimizing processes or adapting it if deviations occur and thus enable decision support. To demonstrate that this approach is suitable for a wide range of different continuous processes, the digital shadows and algorithms for optimization are exemplified at various stages throughout two different process chains.

The first process chain consists of only one process, namely, the extrusion of plastic profiles. In profile extrusion, raw thermoplastics are melted and homogenized using a rotating screw and formed into a continuous profile using an extrusion die.

The second process chain describes typical metal processing from which three processes are selected as examples: hot rolling, tempering, and fine blanking. In hot rolling, the material is heated up and then the thickness of metal sheets or coils is reduced by passing through one or more pairs of rolls. After rolling, the material is heated up to a defined temperature for a certain period. This heat treatment process, called tempering, aims to reduce the hardness of the material. Depending on the final product, a wide variety of sheet metal working processes such as fine blanking can be applied. In fine blanking, the material, either sheet or coil, is punched using a punch and counterpunch to produce components with high sheared surface quality.

Figure 13.1 shows the two process chains and the general structure of the decision support systems. The two process chains are each described separately. After a brief introduction to each process respectively process chain, the prerequisites for digital shadows are presented including numerical and physical models and data acquisition. Finally, concrete examples show the potential of Machine Learning (ML), more precise Reinforcement Learning (RL), in the development of decision support systems.

Finally, the most pertinent results of the different applications are summarized and a brief outlook on the next steps is given.

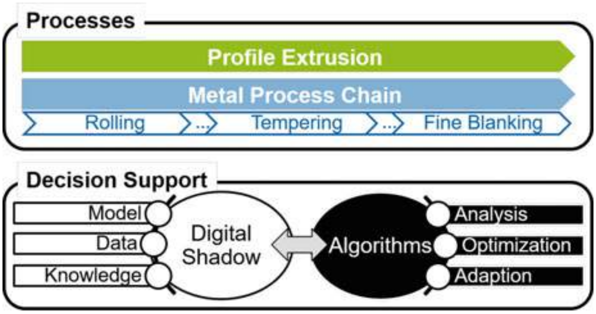

Fig. 13.1 Overview of the continuous processes (top) and the proposed structure of the decision support system (bottom)

13.2 Single Process for Plastics: Profile Extrusion

In the plastic profile extrusion chain, plastic pellets are continuously processed to plastic profiles of fixed cross-sectional shape, (see Fig. 13.2). In a first step, the plastic pellets are melted and homogenized inside the single-screw extruder. The melt is then shaped into the specified profile geometry within the so-called extrusion die. Subsequent to the extrusion die, the so-called extrudate exits the die, where it is still too hot to hold its shape by itself. Thus, the profile is cooled down so that the material solidifies and is fixed in shape. This process step is referred to as the calibration and cooling stage.

Extruded profiles need to show minimal warpage and predictable shrinking behavior to meet market requirements with regard to geometrical, mechanical, and optical properties. The materials typically modeled in profile extrusion are thermoplastic melts. Due to their complex molecular structure, these melts are sensitive to temperatures and shear rates, but often depend additionally on past deformations. This makes it not only difficult to design and set up the process but also challenging to numerically model these materials. The die design, for example, is still largely empirical and based on experience and manual labor.

In the context of this contribution, the die design and the calibration unit will be discussed in more detail. In the design process of extrusion dies, the complex boundary conditions and material parameters should already be taken into account in the numerical design, so that, for example, by providing a mostly uniform melt distribution, the deviation between the target and extruded geometry is minimized. In case of the calibration unit, many material, process, and environment factors influence the cooling of the material and thus can lead to undesired shrinkage and deformation. When it comes to avoiding these undesired behaviors, decision support systems are of great value to adapt the process at process time. Decision support systems require a digital interface between the profile extrusion line, servers, and databases, which many legacy machines are still lacking. Therefore, a modular, portable, and affordable measurement system is presented in the next section, before a numerical simulation model for plastic melts is introduced as a second means of gaining insights into the process.

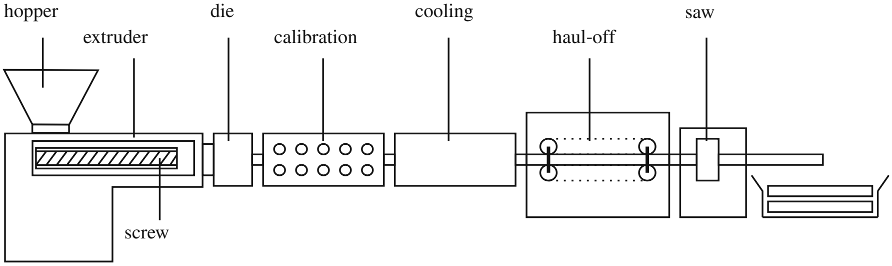

Fig. 13.2 Process sections in a classic extrusion process (Hilger and Hosters 2022)

13.2.1 Prerequisites for Digital Shadows

Besides classical process modeling, data acquisition is one of the key ingredients for the creation of digital shadows. On the one hand, the collected data can be used to monitor and analyze the process during operation, while on the other hand, it can be used to create data-driven models, e.g., as decision support systems. Usually, sensors are used to represent the reality in terms of specific physical values. One challenge is to select suitable data to enhance the digital shadow. Another challenge is the analysis of the measured data to gain more knowledge for further process optimization. In the following, data acquisition will be explained on the basis of profile extrusion.

New extrusion lines are already equipped with the hardware and software requirements for Industry 4.0 applications. However, due to their modular and robust structure, extrusion lines have a long life expectancy, as single parts can easily be repaired or replaced. This results in a large amount of legacy machines in production (+20 years old (Urbanek and Saal 2011)), in particular in small- and medium-sized companies, which are not equipped for data-driven problem analysis and control. Even the most basic vital signs of the extrusion process, the melt temperature, pressure, and motor load (Pilar Noriega and Rauwendaal 2019) are not routinely stored for longer-term analysis. Therefore, retrofit solutions in the form of modular measurement systems connected to a database present themselves as a convenient way to enable data collection in existing extrusion lines.

The first step was the development of such a modular, portable, and affordable measurement system, enabling the retrofit of existing analog extrusion lines, managing the general quality of the manufactured plastic parts, and collecting data for the construction of Reduced Order Models (ROMs) (Sasse and Hopmann 2021). The measurement system as shown in Fig. 13.3 is based on a mini computer and is capable of processing both analog and digital online and off-line data, such as the temperature (e.g., of barrel, melt, die, or extrudate), pressure (e.g., of gear pump or melt filter), rotational speed (e.g., of screw, melt pump, or haul-off), the thickness of the extrudate (by tactile, capacitive, radiometric, or optic methods), power (of cooling setup or motors of extruder or gear pump), piezoelectric sensors (for acceleration, forces, and dynamic cavity pressure), throughput (melt output or

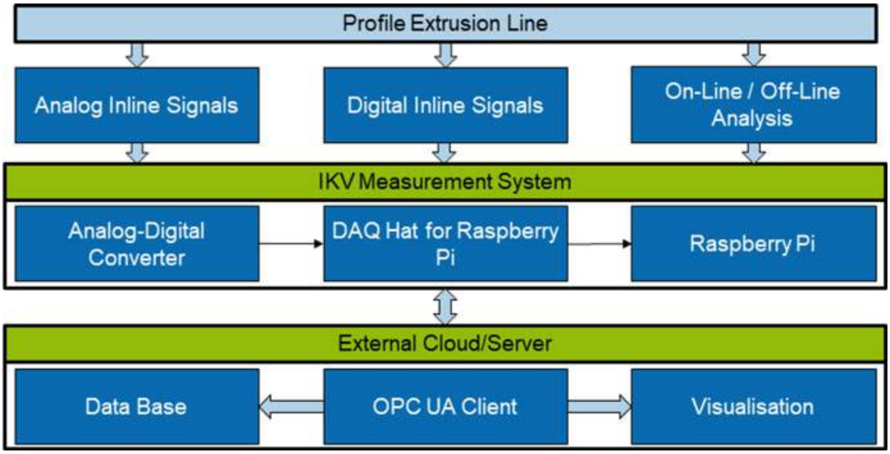

Fig. 13.3 Structure of the modular, portable, and affordable measurement system

raw material input at feed hopper), or camera data. All data is processed by an Open Platform Communications (OPC) Unified Architecture (UA) client, where they are written into a common SQL-based database. Options for real-time visualization, for example, via the open-source software Grafana, are also available. Analysis of the process data is important to determine the influence of variations of process parameters and material properties (Pilar Noriega and Rauwendaal 2019), but a full problem analysis of the extrusion process is only possible with data from all timescales (milliseconds to hours/days). Saving the process data to a common database also has the side effect of added traceability of products for quality control purposes. Based on this working technical infrastructure, the measurements can be aggregated and analyzed and thus used to improve the process. In addition, the OPC UA client provides an interface for operations on external devices, such as computing clusters. This decentralized approach is a suitable method to deploy the decision support system for profile extrusion lines. Within the presented setup, a decision support system cannot only utilize archived process data from the common database but also live process data via the OPC UA client for best results.

While the aforementioned strategy allows insights into the process during operation, some data cannot be acquired by measurements. This may, e.g., be the case if certain parts of the machine are not accessible for the measurement devices, or if the measurement device would influence the process operation, e.g., inserting a temperature sensor into a very small extrusion die flow channel. In these cases, numerical simulations can be used to gain additional information about the quantities of interests in the processes. The availability of stable numerical solution strategies for analyzing the physical models is thus also crucial for the creation of decision support systems. The computed numerical results can serve as high-fidelity data for training or validating the reduced models that form the core of the digital shadow of the production process. Moreover, they enable to tackle more complex tasks like optimization of machine components that cannot be solved by only considering measurement data.

One example, where the ability to accurately model the flow inside profile extruders is important, is the design of new die geometries. As the melt's complex behavior quickly exceeds an engineer's design intuition, the design of such dies can be accelerated by numerical optimization. The main quantity of interest here is the spatially varying velocity field, but also the pressure field and other secondary quantities like shear stresses at the walls can serve as optimization objectives (Hopmann and Michaeli 2016). Consequently, the precise numerical prediction of these quantities inside the flow channel is of great interest. To describe the viscous flow of plastic melts, the corresponding physical Partial Differential Equation (PDE) model is given by the stationary Stokes equations (conservation of momentum) and the stationary continuity equation (conservation of mass):

$$-\nabla \cdot \sigma = \mathbf{0} \qquad \text{and} \qquad \nabla \cdot \boldsymbol{v} = \mathbf{0}, \tag{13.1}$$

where $\boldsymbol{v}$ denotes the unknown velocity and σ the Cauchy stress tensor. This stress-based formulation originates from continuum mechanical considerations and is often written in terms of the unknown quantities, namely, velocity $\boldsymbol{v}$ and pressure p:

$$\sigma = -p\mathrm{I} + 2\eta\epsilon, \qquad \text{with} \qquad \epsilon = \frac{1}{2}(\nabla\boldsymbol{v} + \nabla\boldsymbol{v}^T). \tag{13.2}$$

Here, η is the dynamic viscosity and ϵ denotes the rate-of-strain tensor. While many Computational Fluid Dynamics (CFD) applications assume a Newtonian fluid, where the viscosity is a constant material property, in our application, we need to account for the shear-thinning characteristics of molten plastic, i.e., the viscosity decreases with increasing shear rate. In order to model this behavior, there exists a variety of constitutive equations in the literature. For our application, we have chosen the Carreau-Yasuda model as it proves to be in good agreement with measurements for a wide range of shear rates (Hopmann and Michaeli 2016).

Together with the closure equations Eq. (13.2) and this material law, Eq. (13.1) forms a nonlinear PDE system, for which no closed-form analytical solution can be found. Thus, we employ the Finite Element Method (FEM) to compute a solution numerically (Tezduyar et al. 1992). Figure 13.4 exemplary shows the solution of a heat conduction equation computed inside an extrusion die's flow channel on the left-hand side as well as the computational mesh, used for computing the temperature distribution on the right-hand side.

Applying FEM to Eq. (13.1) provides high-fidelity solutions for the unknown velocity and pressure fields, which can then, e.g., be used to evaluate an objective function describing the desired target properties or constraints that have been posed on the design process. More precisely, for the design of flow channels in extrusion dies, one primary design constraint can be the homogeneity of the flow velocity at the die exit. Here, different objective functions have been proposed in the literature (Elgeti 2011; Rajkumar 2017). All of them have in common that they divide the

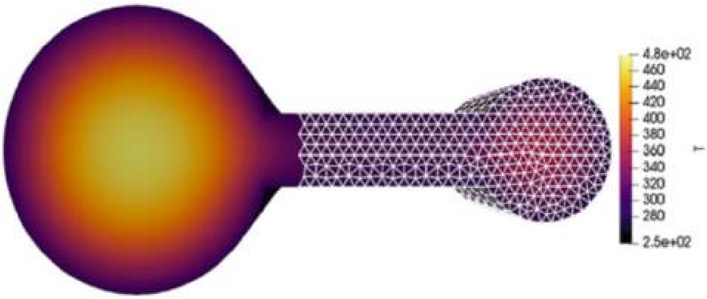

Fig. 13.4 Exemplary computational mesh and corresponding FEM solution of the temperature distribution in an extruded profile

outflow of the extrusion die into multiple patches over which an average velocity is computed. This is afterward compared to the average velocity over the whole outflow boundary. In order to compute these averages, a knowledge of the spatially varying velocity field is required, which proves the importance of proper numerical modeling for the context of shape and design optimization.

In the following section, we will present a first proof of concept, how a two-dimensional extrusion die geometry can be optimized using Reinforcement Learning.

13.2.2 Shape Optimization with Reinforcement Learning

Decision support systems should suggest one or multiple possible solutions to a problem. This oftentimes requires solving optimization tasks. In practical applications in real-world use cases, it is often more interesting to find reasonably good solutions in a short time than to search for the optimal solution for a long time. To accommodate this, many different approaches have been developed. Among these, RL is emerging as an additional method, whose feasibility is currently being investigated for a variety of optimization tasks (Samsonov et al. 2020, 2021; Kemmerling et al. 2020). When confronted with a set of problems which exhibit similarities, but are not identical, classical optimization approaches typically solve each problem individually, without taking advantage of the shared structure between the problems. In an RL approach, however, this shared structure can be exploited by training an agent which learns a general strategy to solve incoming problems. Once learned, this strategy can then be applied to many problems at comparatively small computational cost.

A wide variety of optimization problems emerges from production contexts, including scheduling problems, layout design of shop floors, and tool design. In this section, the focus is placed on tool design in profile extrusion settings as an illustrative example, although the approach is transferable to a wide variety of tool design tasks.

As mentioned before, one of the remaining challenges in profile extrusion is the shape optimization of flow channel geometries with the aim of minimizing shrinkage and warpage in the produced parts, hence improving product quality. Although this problem concerns the construction of tools and does not require real-time optimization capabilities as they would be needed in a production context, it demands numerical high-fidelity solutions from computationally expensive CFD simulations. This incentivizes the application of efficient optimization approaches.

In this work, the environment corresponds to the digital shadow (Bergs et al. 2021) of an extrusion die, and the agent can modify the shape of the flow channel in an iterative manner. More specifically, it can deform the computational mesh of the die geometry by moving individual control points of a spline, which is used to transform an initial mesh – a method known as Free Form Deformation (FFD) (Sederberg and Parry 1986). This type of geometry parameterization allows for a relatively low number of design parameters while simultaneously offering flexibility with respect to the resulting shapes as well as guaranteeing smooth deformations if the spline is chosen appropriately. To generate the observations, we solve the numerical model presented in Sect. 13.2.1 using FEM and provide the results to the agent.

The geometry modifications of the agent need to adhere to certain constraints so that the resulting tool design fulfills its intended function. To show the feasibility of the approach, the agent is trained to optimize a T-shaped geometry with one inlet and two outlets, which is inspired by the separation of the melt flow inside a coat hanger distributor. The agent's objective is to modify this geometry such that a certain mass flow ratio between the two different outlets is achieved. During each episode, the agent is provided with a new ratio for which the geometry is supposed to be optimized. After a certain number of steps during the training, the agent is evaluated on a set of unseen goal ratios to estimate its learning and generalization progress. The results of the training and the validation of an agent trained with the Proximal Policy Optimization (PPO) algorithm (Schulman et al. 2017) are depicted in Fig. 13.5. As one can see, the agent learns a strategy for achieving the desired goal ratios, leading to a decrease of the number of steps per episode and an increase of the average cumulative reward per episode. Here, an incremental shape optimization strategy has been chosen, where one timestep corresponds to one action, i.e., a single modification of the geometry. After just roughly 400 episodes (corresponding to 400 different goal ratios), the agent consistently receives an average cumulative reward greater than 5 (highlighted by the area shaded in dark blue), indicating successfully accomplished goals. Even for previously unseen mass flow ratios, the agent's performance consistently improves as shown in Fig. 13.5b, allowing to accomplish 4 out of 5 validation runs at the end of training.

The approach presented here forms the basis for further research, e.g., investigating additional, more complex geometries and incorporating more realistic optimization criteria such as the flow homogeneity.

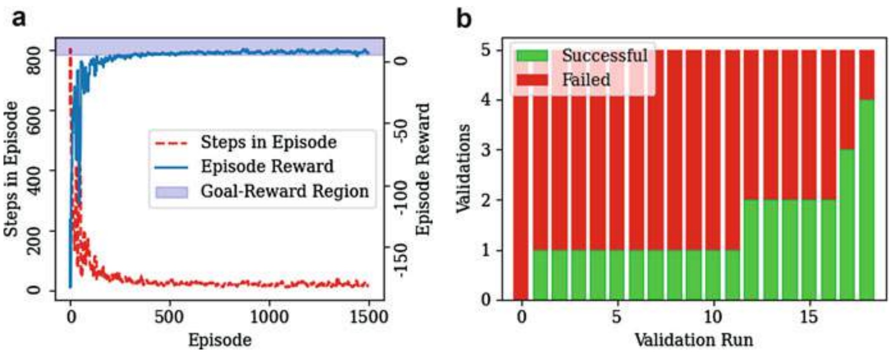

Fig. 13.5 Training progress (**a**) and the success rate of the validation runs (**b**) for a PPO agent following an incremental shape optimization strategy. The area, where the cumulative reward is greater than five, is shaded in blue, indicating that the agent achieved its goal. The training is stopped after reaching 1500 episodes

13.3 Metal Processing Process Chain: Rolling, Tempering, and Fine Blanking

As already mentioned, the relationships and interactions between material, process parameters, and the final properties are not always known, although continuous processes such as rolling have been used for a long time and are well-established. Here, digital shadows in combination with various algorithms can support process experts in their decision-making process. Such decision support systems can lead to further optimization of processes and complete process chains. In this chapter, the development of digital shadows and application of data analysis and optimization algorithms are shown for selected examples of processes along a metalworking process chain. First, the steps necessary to develop a digital shadow are presented. As an example of the use of process models in the context of digital shadows, physical models are presented for hot rolling and tempering that can provide real-time information on the microstructure and thus on the final mechanical properties. Processes that follow tempering, such as press hardening, are not considered further here for the time being. Subsequently, cold rolling and fine blanking are used to demonstrate how data from processes can be integrated and processed so that conclusions can be derived about the final product properties (see Fig. 13.6). Finally, an exemplary decision support system is presented. Concretely, the previously presented physical model of hot rolling is combined with reinforcement learning methods to optimize process parameters.

13.3.1 Prerequisites for Digital Shadows

In this chapter, the prerequisites for developing digital shadows are presented on the basis of some selected processes of a complete metal processing process

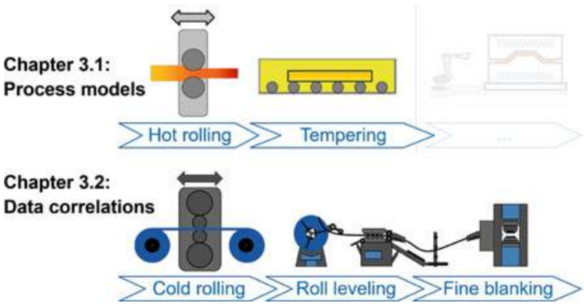

Fig. 13.6 Selected processes of the metal processing process chain

chain. More specifically, the potential of physical and semiempirical models for the prediction of product quality such as mechanical properties will be demonstrated using the example of hot rolling and tempering processes. Subsequently, it will be shown that process data analysis enriches digital shadows. Process data from cold rolling and fine blanking can be meaningfully aggregated and used to draw conclusions about material and tool behavior.

13.3.1.1 (Hot) Rolling + Tempering

In the following, the abovementioned processes are briefly presented, starting with rolling. Rolling is a widely used and established metal forming process employed in several industrial sectors, e.g., the automotive industry. A rolling process produces semifinished or finished products with customer specified geometry and mechanical properties. About 95 % of steel products undergo at least one rolling process during their production (Allwood et al. 2012). Rolling consists of several steps, called passes, in which the material's thickness is reduced by moving it through two opposing rolls. In hot rolling, the material is heated above a material-specific recrystallization temperature (for steel typical 1000 °C–1200 °C) and then deformed. Therefore, the microstructure and thus product quality like the mechanical properties can be directly influenced (Lenard et al. 1999).

After rolling, the rolled materials undergo heat treatment. According to DIN 10052 (1994), heat treatment is defined as a temperature-time cycle for desired characteristics of materials or workpieces. Among all the heat treatments, quenching-tempering combination is aimed to optimize the properties, e.g., hardness and toughness of material for end use or for the following process. But the material also loses its toughness, which makes it not applicable for the further processing, therefore a reheating and holding at a temperature below a certain temperature. This process is called tempering and it is applied after quenching as a following step for regaining toughness with limited loss of hardness. Several factors have impacts on steel properties during tempering. Among them, temperature and time are the most important factors for tempering treatment. With designated temperature and proper holding time, the microstructure and thus the mechanical properties can be controlled. This affects the subsequent process such as press hardening.

First, a physical model for hot rolling is described and then for tempering. Due to the widespread use of hot rolling processes and their high complexity, modeling approaches were developed early on. The development goes back to the 1920s of the last century, where von Kármán (1925) and Siebel (1925) used basic mechanics to describe and analyze the rolling process. Based on their fundamental findings, known as the slab method, Sims published simplified equations to predict roll forces and roll torques (Sims 1954). These simplified mechanical models are able to calculate complete processes within several seconds; therefore, they are known as Fast Rolling Models (FRMs). These FRMs are often combined with semiempirical material equations to describe the microstructure. There are many similar models described in the literature. One well-known and typical FRM is SLIMMER (Beynon and Sellars 1992) which uses a thermal, a microstructure, and a mechanical model (Sims 1954) to predict roll forces, torques, and the microstructure evolution during multi-pass hot rolling. As mentioned in Sect. 13.1, one challenge is to predict product quality during the process. To achieve this, suitable process models must be linked with other data sources in the sense of a digital shadow. Here, an existing FRM, developed at the Institute of Metal Forming (IBF), is used for convenience (Lohmar et al. 2014). The model consists of several modules, predicting the deformation, the temperature, and the microstructure evolution as well as rolling forces and torques. However, it does not predict mechanical properties after rolling which would be essential for the prediction of the product quality. For this purpose, the model was extended by additional equations calibrated for a structural steel S355.

For the prediction of mechanical properties such as Yield Strength (YS) and Ultimate Tensile Strength (UTS), three extensions are implemented. First, the cooling of the material after rolling until the microstructure transformation of austenite γ to ferrite α is calculated. Second, at the transformation, austenite grain size d_γ is converted to a ferrite grain size d_α. Third, based on d_α and calibrated material parameters, predictions on YS and UTS are made.

For the cooling after rolling until the transformation temperature, a one-dimensional finite-difference method, which considers heat conduction inside the rolling stock, radiation, and convection on the surface, is used. For the phase transformation, from austenite d_γ to ferrite d_α, equations according to Hodgson and Gibbs (1992) and their parameters are used.

Based on d_α and Eq. (13.3) formulated by Hodgson and Gibbs (1992) and Singh et al. (2013), YS and UTS are predicted. YS and UTS are calculated based on the chemical composition-dependent solid solution strengthening σ_{SS} and grain-boundary (Hall-Petch) relationship. In addition to the YS prediction, the strain hardening due to the dislocation density $\sigma_{DIS_{YS}}$ is also accounted:

$$YS = \sigma_{SS_{YS}} + \sigma_{DIS_{YS}} + K_{YS} \cdot d_\alpha^{-0,5}, \quad \text{and} \quad UTS = \sigma_{SS_{UTS}} + K_{UTS} \cdot d_\alpha^{-0,5}. \tag{13.3}$$

Next, the FRM predictions regarding grain sizes and mechanical properties are compared to experimental data (see Fig. 13.7). For this, a S355 slab was heated up to 1200 °C and hot rolled from an initial thickness of 140 to 25 mm in eight

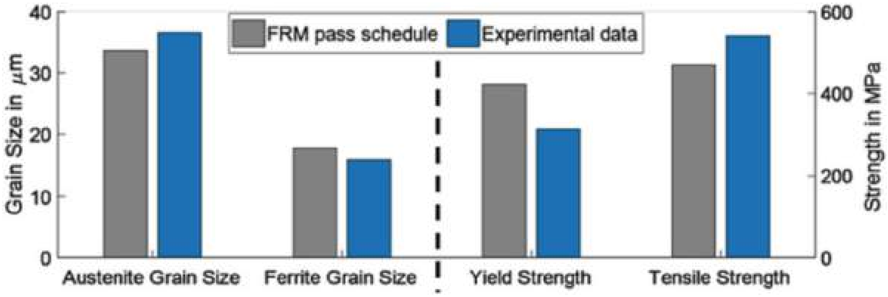

Fig. 13.7 Comparison between the measurements and FRM-predicted values

passes. First, the average former d_γ and d_α from the experiment are compared to the FRM prediction. Both predicted grain sizes agree well with the measured ones and differ only by a few µm. Finally, tensile tests of the samples according to ISO 6895 are carried out using a Zwick Z100 testing machine. The predicted mechanical properties are 35 % higher for YS and 13 % lower for UTS. The noticeable difference in YS might be related to the simplified modeling. Furthermore, a dedicated calibration of the YS and UTS parameters for S355 structural steel should improve the accuracy of the FRM. All in all, it becomes evident that fast models can provide accurate results in real time that usefully complement digital shadows.

The results of this model, such as the final microstructure, can then be passed as input to the next process model so that more accurate predictions can be made. Here, hot rolling is followed by tempering. Therefore, a physical and semiempirical model for tempering is presented. Numerous tempering models are introduced in the recent years (Lee and Lee 2008; Jung et al. 2009; Smoljan et al. 2010). However, these models cover only few aspects of the quenching and tempering process with limited calculation speed, which cannot fulfill the purpose of digital shadows. Therefore, it is ideal to introduce whole scale, real-time tempering models which can be utilized for process monitoring and optimization without significant sacrifices to the accuracy.

There are several mechanisms that are contributing to the yield strength of a material. Here, the two most important are the dislocation hardening σ_{disl} and precipitation hardening σ_p. The dislocation density contribution is given by the Taylor equation (Kocks and Mecking 2003) accounting for the dislocation forest hardening:

$$\sigma_{\mathrm{disl}} = \alpha M b^2 \sqrt{\rho}. \tag{13.4}$$

The precipitation contribution to strength arises from the Orowan mechanism of hardening: (Smallman and Ngan 2014)

$$\sigma_p = \frac{0.26\mu b}{R} \sqrt{f_p} \log\left(\frac{R}{b}\right). \tag{13.5}$$

The yield strength of the material can therefore be predicted at any point in the process by having access to the internal microstructural variables such the dislocation density ρ precipitate fraction f_p and radius R.

The change in dislocation density as a function of the lath width is given by the closed relationship (Galindo-Nava and del Castillo 2015):

$$\rho = \frac{3E}{(1+2\nu^2)\mu} \frac{4\epsilon^2 d_{cottrell}}{d_{lath}^2 b}. \tag{13.6}$$

The precipitation reactions are modeled based on the precipitation phenomenology described in Deschamps and Brechet (1998). The model calculates the time evolution of the precipitate radius and the number of precipitates which can be used directly in Eq. (13.5). The model was evaluated for the tempering behavior of a hot rolled MMnS. The material was tempered at various temperatures and times, and the effects of the process were evaluated utilizing microhardness testing. Figure 13.8 shows the predicted evolution of the material hardness, for various temperatures and times, compared with the experimental measurements. The MMnS exhibits typical tempering behavior which is characterized by a steep drop-off at the beginning followed by a logarithmic reduction in the hardness. The model at its current state is able to predict quite accurately the hardness evolution at short and long times. The biggest deviations are encountered in the lower temperature regime where potentially the presence of metastable carbides is potentially not accurately predicted.

13.3.1.2 Data Analysis of the Fine Blanking Process

In addition to the model-side description over process borders, as presented earlier for hot rolling and tempering, data over several processes can also be correlated with certain properties. Here, fine blanking is chosen as an exemplary sheet metal

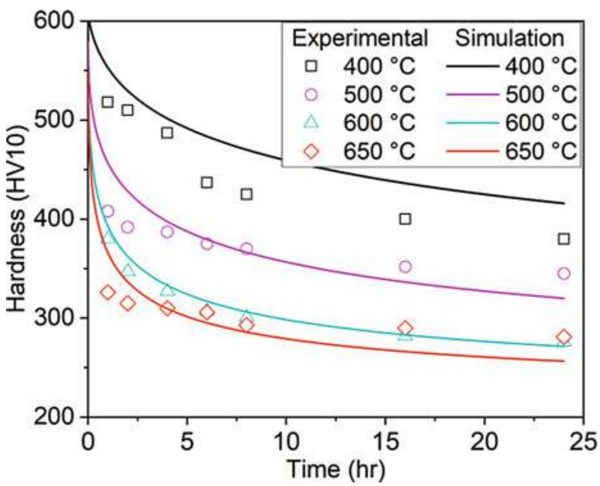

Fig. 13.8 Comparison of experimental and simulated hardness for tempered medium manganese steel

forming process because it is the most frequently used precision cutting process in industry (Zheng et al. 2019). Fine blanking is a manufacturing process for the cutting of metallic components. It is similar to blanking in a single-stroke shearing process, but is extended by a blank holder and a counter punch to improve the quality of produced component (Klocke 2017). Areas of application for the fine blanking process arise when there are special requirements with regard to the contact area of the cut surfaces (smooth cut), the perpendicularity of the cut, as well as the achievable dimensional and form tolerances.

The process chain prior to fine blanking comprises different steps depending on the material. Hot-rolled and cold-rolled strips account for the largest share of the fine blanking material. In this example, cold-rolled material is used as an input for fine blanking (see Fig. 13.9). Due to the complexity of the interactions along the process chain and in the fine blanking process, the relationships between the processes are not fully understood. With an enabled IoP process, signals along the process chain can be acquired and analyzed in high quantities. The challenge is to aggregate the data and analyze it in such way that decision support can be deduced. To underline the potential in a detailed monitoring of the fine blanking process, large series of fine blanking strokes were conducted and analyzed for wear detection. The information of the tool wear at the fine blanking process will enrich the digital shadow of the fine blanking process and is a first step to enable decision support along the process chain.

For wear detection, data is acquired by nine piezoelectric sensors, which have been integrated into the tool structure to measure all process forces including punch, counterpunch, and blank holder force (Niemietz et al. 2020) and with acoustic emission sensors that have been applied to the upper pressure plate close to the punch positions (Unterberg et al. 2021). The raw sensor signal is first cleaned and subsequently segmented into the stripping phase where the sheet metal is stripped off the punch. This phase is of special importance since tensions during stripping are a primary indicator for damage of the tools, coating, and geometry. In order to model the variation in the signal of a wear-sensitive process phase, the stripping of the sheet metal off the punch, autoencoders have been utilized that are able to learn a typical force-time curve automatically (Niemietz et al. 2021). In short, a convolutional autoencoder is used to convolute and devoncolute the input time series

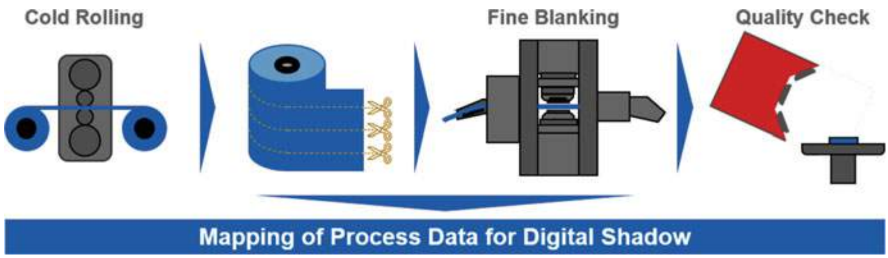

Fig. 13.9 Process chain: cold rolling and fine blanking

through a bottleneck and reconstruct the original signal utilizing the mean squared error between the original input time series and the reconstructed output signal as the loss function. The presented evaluation is based on this loss function also known as reconstruction error. The hypothesis is that the development of this error over time throughout stroke series of several thousand strokes can indicate changes in the wear conditions of important tool components.

The study utilizes four experiments with about 2000–3000 strokes per experiment. For all experiments, the wear increase has been observed to be high in the first part of the experiment and near zero in the second half of the experiments.

The results presented in Fig. 13.10 on the left show the qualitative change of the force signals in the stripping segment over time. Stick-slip behavior can be observed for the first thousand strokes but is not observable for the later strokes. Similarly, the reconstruction error, especially for experiments 2 and 4, shows high values for the first part of the experiment but to stabilize later in the experiments. The cumulative error clearly shows the similarity to a logarithmic behavior. Both observations match the observed wear increase in the beginning and end of the experiment execution. The presented plots are found representative for several series of experiments conducted with the fine blanking process. In summary, using a very shallow noncomplex autoencoder, the amount of error in the learned encodings seem to be an indicator for wear increase during fine blanking.

While the presented study is a first step to decode the dependencies within process signal variations with physical quantities of interest, the verification of the approach has to be conducted on larger and more heterogeneous experiments. Nevertheless, the force data can be used for wear detection and is thus can be used to enrich the digital shadow of the fine blanking process.

But the process is influenced by numerous other parameters such as material parameters that are defined in upstream cold rolling processes, or lubrication setup. Especially the mechanical properties of the material are varying along the coil. Typically, material properties are only measured at the beginning and end of the

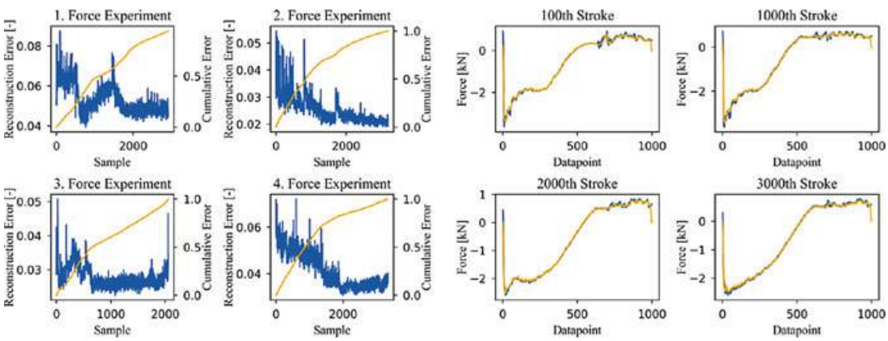

Fig. 13.10 (**a**) The (cumulated) reconstruction errors are presented. (**b**) Selected strokes of the second experiment are presented that are representative for the change in the force signal of the stripping segments (Niemietz et al. 2021)

coil; therefore, there is no information about the exact material properties along the coil. This does not allow any conclusions to be drawn about the material quality in the event of defects in the fine blanking process. Thus, in an enabled IoP, the cold rolling-induced material variations could be monitored by monitoring the upstream processes to optimize the fine blanking process.

13.3.2 Process Design and Optimization with Reinforcement Learning

Due to its high industrial relevance, even small optimizations of the rolling process have a significant effect regarding energy and material consumption (Allwood et al. 2012). One factor that affects the (hot) rolling process efficiency is the process design (pass schedule) which defines all process parameters for each pass, e.g., the height-reduction and inter-pass time. Pass schedules are generated by complex heuristics designed by experts based on their experiences and with the support of FRMs or FEM simulations. Historically, pass schedules where laid out by iterative approaches where maximum allowable height reduction was applied until the desired thickness was reached (Pietrzyk et al. 1990). Additionally, there were first efforts to use genetic algorithms (Hernández Carreón et al. 2019) for multi-objective optimization.

Designing pass schedules in hot rolling processes (see Sect. 13.3.1.1) is a time-consuming process typically performed by domain experts. As described in Sect. 13.2.2, RL is a promising approach for a wide variety of optimization settings in production, including the automated design of pass schedules, where it could potentially uncover novel scheduling strategies. One of the requirements of RL is access to a simulation, since training an agent on the real process would be prohibitively costly and time-consuming. Instead of computationally expensive FEM simulations, a FRM (see Sect. 13.3.1.1) can be used in the hot rolling context to arrive at simulation results within seconds rather than in minutes. A given model can be enhanced with new measurements, allowing for digital shadows (Bergs et al. 2021) in the hot rolling context to be easily extended.

As in many domains, simulation models such as FRM often contain the intellectual property of the relevant stakeholders, which may be reluctant to share the details of their models because they offer a competitive advantage. When third-party machine learning experts want access to such models in the context of a World Wide Lab (WWL), this can pose a problem. However, implementing machine learning solutions does not necessarily require the FRM itself, but only access to it, i.e. the ability to query the corresponding output to input fed into the model. In the approach investigated here, this is accomplished with a Simulation-as-a-Service (SaaS) architecture first introduced in Scheiderer et al. (2020), where a suitable interface is deployed on the infrastructure of rolling mill operators, which can access the FRM internally and can provide simulation outputs when queried by other stakeholders within the WWL. Beyond the scope of this use case, such SaaS architectures can generally serve as enablers to the IoP wherever giving third parties

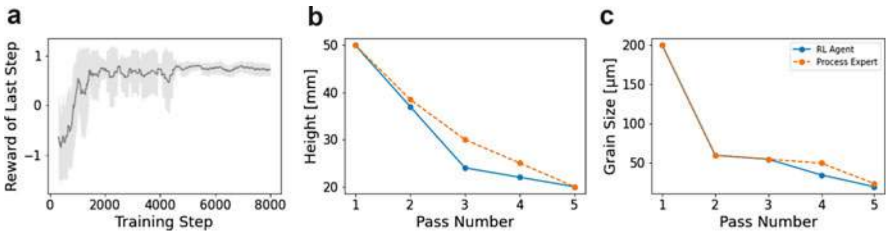

Fig. 13.11 (**a**) Training progress of a SAC agent on the rolling task shown as the rolling mean of the received reward with the shaded region showing the rolling standard deviation. (**b**) Height and (**c**) grain size of material throughout pass schedule generated by a trained RL agent and a pass schedule created by a process expert. (Adapted from Scheiderer et al. 2020)

access to the internals of a simulation model is undesirable, but providing access to simulation inputs and outputs is not problematic.

The proposed architecture is validated (Scheiderer et al. 2020) by training a SAC agent (Haarnoja et al. 2018) to create pass schedules of a fixed length by controlling the roll gap and pause time in a hot rolling scenario. Rather than providing the agent with direct access to the simulation, it indirectly interacts with it through the SaaS architecture. The agent trained in this way shows good convergence behavior as shown in Fig. 13.11a and generates reasonably good pass schedules compared to those created by domain experts (see Fig. 13.11b, c). While this work shows the general feasibility of the approach, many opportunities for improvement remain unexploited. These include improving upon the current design of the reward function, learning from pass schedules generated by experts and investigating the transfer of trained agents to scenarios with different material properties.

Next to Sect. 13.2.2, where the applicability of RL for tool design was demonstrated, this section additionally shows the potential of RL in process design as exemplified by hot rolling scheduling. The ability to produce schedules similar to those created by human operators very quickly can be valuable in many other process design problems as well. Ultimately, such approaches may serve to realize the vision of the IoP by enabling networks of virtual agents, which can dynamically respond to changing requirements from other components in the network.

13.4 Conclusion and Outlook

In this contribution, throughout two different process chains with continuous processes, different stages are presented that enable decision support. A suitable basis for this are digital shadows. Therefore, the development of the digital shadows is first given by a detailed description of numerical, physical, and semiempirical models. For instance, rolling and tempering models are shown that predict in real-time product properties such as yield strength or hardness. The comparison with measurement shows that the results of these models can make a valuable contribution to digital shadows. However, the parameters for the semiempirical equations have to be determined very precisely; otherwise, the predictions deviate too much.

In addition to models, digital shadows need process data in real time. Therefore, a modular concept for data acquisition, aggregation, and processing is demonstrated on the example of a typical extrusion line. The concept shows how both analog and digital signals can be recorded with simple and low-cost equipment and systematically stored in a database using the well-known standard OPC UA. Systematically stored process data is very useful, as shown by the example of fine blanking. Based on the time-series data from the stamping force sensors, convolutional autoencoder is used to extract patterns in order to detect wear. The results show that such a data-driven approach is promising and generally suitable to study the highly complex interactions between process parameters and product quality. For this reason, further research is ongoing with the aim of using the insights gained for process optimization.

For a decision support system, however, more is needed. For both process chains, model data is coupled with reinforcement learning to optimize the shape of either process components or process parameters. For the profile extrusion use case, the optimization of a T-shaped geometry represents a flow channel in profile extrusion in order to minimize shrinkage and warpage. The algorithm modifies the geometry of the flow channel by moving individual points of a spline. In the future, the approach will be extended to include more complex geometries and incorporate flow homogeneity as optimization criteria.

In summary, it can be stated that the general approach is independent of the process. Especially the optimizations by coupling model data with reinforcement learning show this very clearly. The concrete implementation, however, requires detailed process knowledge and is only directly transferable to other processes to a limited extent.

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Modular Control and Services to Operate Lineless Mobile Assembly Systems

14

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Abstract

The increasing product variability and lack of skilled workers demand for autonomous, flexible production. Since assembly is considered a main cost driver and accounts for a major part of production time, research focuses on new technologies in assembly. The paradigm of Line-less Mobile Assembly Systems (LMAS) provides a solution for the future of assembly by mobilizing all resources. Thus, dynamic product routes through spatiotemporally configured assembly stations on a shop floor free of fixed obstacles are enabled. In this chapter, we present research focal points on different levels of LMAS, starting with the macroscopic level of formation planning, followed by the mesoscopic level of mobile robot control and multipurpose input devices and the microscopic level of services, such as interpreting autonomous decisions and in-network computing. We provide cross-level data and knowledge transfer through a novel ontology-based knowledge management. Overall, our work contributes to future safe and predictable human-robot collaboration in dynamic LMAS stations based on accurate online formation and motion planning of mobile robots, novel human-machine interfaces and networking technologies, as well as trustworthy AI-based decisions.

Keywords

Lineless mobile assembly systems (LMAS) · Formation planning · Online motion planning · In-network computing · Interpretable AI · Human-machine collaboration · Ontology-based knowledge management

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14.1 The Future of Assembly

Assembly accounts for up to 44 % of production costs and 70 % of production time and is therefore an essential step in the production process chain and impacts the efficiency of production (Lotter and Wiendahl, 2013). It has been postulated for several decades that conventional, fixed-coupled assembly systems are reaching their limits of adapting to dynamic changes, such as fluctuating market requirements and the production of customer-specific products down to batch size one (Hu, 2013). Fluctuations in supply chains and production capacity resulting from global crises increase the pressure for sustainable and crisis-resistant production (Hiscott et al., 2020). The introduction of sustainable product portfolios, like the transition from combustion-powered vehicles to electric vehicles, leads to expensive assembly reconfigurations (Hubik, 2021). The resulting paradigm shift to dynamically coupled assembly systems promotes and requires the design of flexible and adaptive systems capable of addressing individual assembly sequences and responding resiliently to changing conditions (Hüttemann, 2021). Assembling parts to create individualized products results in a high degree of complexity, primarily caused by the total number of product variants (Asadi et al., 2016). Adaptability can be seen as fundamental to the success of a company and is enabled through Industry 4.0 (I4.0) technologies (Lanza et al., 2018). Shifting from the Industrial Internet of Things (IIoT) and I4.0 to the Internet of Production (IoP) will enable a holistic, cross-domain network and linkage of currently stand-alone industrial technologies, revealing and harnessing the interdependencies of previously separate production steps and technologies.

The **paradigm of LMAS** provides a possible realization of adaptable and flexible assembly and is based on three principles:

1. **clean floor approach**: the assembly operation is executed on a fixture-less and free space, which allows for free placement of assembly resources,
2. **mobilization** of all physical resources (robots, parts, tools), allowing free and autonomous formation of assembly stations, and
3. **dynamic planning and control** creating suitable assembly stations and optimizing schedules, job-routes, and task allocation in dependence on demand and objective function.

LMAS are characterized by a dynamic sequence of operations, which is not fully predetermined for most products, requiring sophisticated planning of scheduling, task allocation, as well as formation and trajectory planning of the mobile robots, to enable efficient operation (Buckhorst et al., 2019).

In the following, we first conceptualize modular levels and layers to operate LMAS highlighting included concepts of the IoP (Sect. 14.2) by summarizing our former research results. This is followed by detailed research focal points (cf. Fig. 14.2) and future research directions of the modules.

14.2 Modular Levels and Layers for LMAS Operation

Creating an operating future assembly system following the paradigm of LMAS requires a connection of currently stand-alone industrial production steps and technologies. The necessary cross-domain network follows the **main principles of the IoP**, namely, the creation of a **World Wide Lab** and an interrelated network of **digital shadows** (Brauner et al., 2022). Accordingly realizing the operation of LMAS requires answering the following **research question**: *How can efficient decision-making, modular field, and process-level control in human and machine factory operation be realized and combined with locally and globally available information (services) and distributed computing capacities, so that a real-time-capable response behavior of a LMAS results?* Answering this research question contributes a modular collaboration of cyber-physical and virtual devices to the IoP, by combining domain-specific benefits and expertise of production engineering, with data analytic and human factors.

This research group has identified necessary functional blocks ("**Holons**[1]") as well as communication, authentication, and safety layers to operate LMAS and structured these into a framework. The resulting framework maps the holons into a **Holarchy** (Buckhorst et al., 2021). In particular, this holarchy defines a semantic framework in which the processes, resources, technologies, and planning steps can be integrated as dedicated holons and related to each other via interfaces and layers, as can be seen in Fig. 14.1.

In the contribution at hand, we detail research results and future research directions of particular holons, based on the application scenario of a truck assembly, as visualized in Fig. 14.2. Beginning with the macroscopic level of formation planning, Sect. 14.3 gives an overview over autonomous decision-making involving capability-based digital shadows to realize planning of the spatial arrangement ("formation") of heterogeneous hardware resources in an assembly station (cf. Fig. 14.2, upper right). This is followed by the mesoscopic level of mobile robot control. Section 14.4 discusses different possibilities for system modeling of commonly utilized robotic manipulators in production lines and introduces appropriate motion planning algorithms for such systems (cf. Fig. 14.2, bottom left). Thereafter, the microscopic level of services, such as in-network computing, interpreting autonomous decisions and input devices is detailed. Section 14.5 addresses the identified need for fast control algorithms by proposing the deployment of In-Network Computing (INC) in industrial environments, hereby outlining major challenges that need to be overcome (cf. Fig. 14.2, bottom right). Subsequently, Sect. 14.6 focuses on extracting relevant information from images using interpretable features learned by generative Deep Learning (DL) methods (cf. Fig. 14.2, bottom center) before

[1] As defined by Van Brussel et al. (1998): "Holon: An autonomous and co-operative building block of a manufacturing system for transforming, transporting, storing and or validating information and physical objects. The holon consists of an information processing part and often a physical processing part. A holon can be part of another holon."

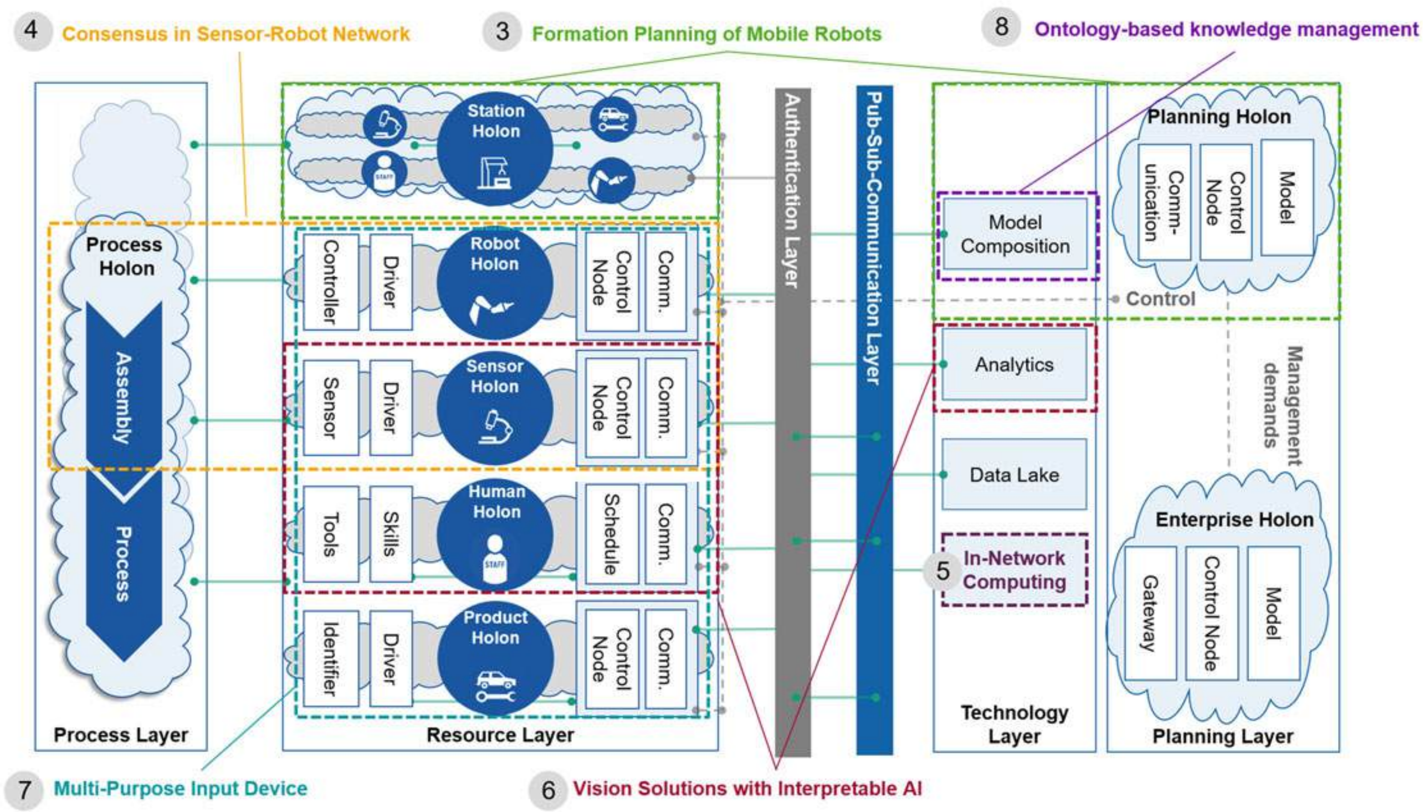

Fig. 14.1 Holarchy of the *Future Assembly* including highlighted research focal points (based on Buckhorst et al. 2021)

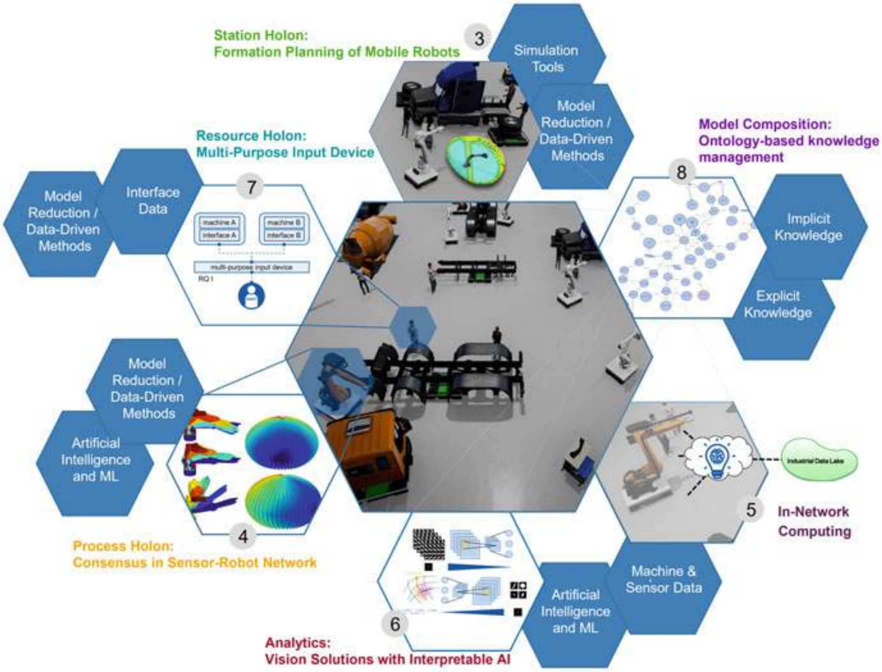

Fig. 14.2 Linking research focal points for operating LMAS with research objectives from the IoP (in blue) exemplified on a scene from a truck assembly

Sect. 14.7 addresses the question of how human-machine interfaces (HMI) should be designed to meet the requirements of usability, production process flexibility, and accounting for robot autonomy in the context of Human-robot collaboration (HRC) (cf. Fig. 14.2, top left). Lastly, Sect. 14.8 presents an approach to developing an assistance system for knowledge-based control process configuration (cf. Fig. 14.2, far right). The research focal points of this chapter are embedded into the following fields of research in the framework of the IoP:

- Assembly planning and control (Planning Layer, Resource Layer)
- Description models and digital twins (Technology Layer)
- Intelligent computation methods (Technology Layer, Resource Layer)

14.3 Toward Modular Station-Level Control Through Formation Planning of Mobile Robots

Reacting to ever-changing demands regarding production volumes and product mix and production disruptions, the assembly *Planning Holon* (cf. Fig. 14.1) regularly recalculates assembly station compositions and placements to execute the allocated assembly tasks, resulting in constantly changing assembly stations (Buckhorst et al., 2022; Kluge-Wilkes and Schmitt, 2021a). Ideally, the *Station Holon* – controlling the assembly stations' operation as a module of the assembly – reconfigures the station to allow for optimal assembly operation in dependence on the allocated assembly tasks. *Station Holons* control a defined set of multipurpose resources (like mobile robots or sensors) on a defined area in the assembly (the assembly station) by allocating tasks to resources and planning the station formation (formation: temporal-spatial layouts of mobile assembly resources in relation to each other and their surroundings).

Present research in the field of mobile robotics mostly focuses on optimizing control algorithms (e.g., in Sect. 14.4) for single robots or the multi-SLAM (simultaneous localization and mapping) problem. In both fields, the goal poses of the robots are assumed to be known. But how are these goal poses determined in the first place? There is a high number of possible goal poses for robots allowing the execution of allocated tasks and accordingly a high number of station formations, necessitating a means of evaluating formations with regard to executability of tasks to select optimized formations. Such an evaluation as a base for formation planning closes the gap between high-level factory planning and low-level robot control.

As a first step, a standardized form of describing resources (here: robots), capabilities, and tasks must be found to realize an allocation of tasks to resource. We developed the CAPability-based resource AllocatioN Ontology (CAPILANO) to describe and match the required capabilities to execute the assembly tasks (like screwing, transporting, or welding) with the capabilities the robots offer (Kluge-Wilkes, 2022). The allocation in CAPILANO is based on a theoretical model of capabilities to perform a task, the spatial executability of allocated tasks needs to be evaluated subsequently. For an overview on evaluation criteria of executability of a task, see Kluge-Wilkes and Schmitt (2021b). By evaluating the workspace according to the quantity of reachable orientations by the robot flange at discrete points, a so-called *Reachability Map* is generated (Dong and Trinkle, 2015). Since this method currently only includes the reachability with regard to the robot flange and excludes tools and equipment (Makhal and Goins, 2018), the **inclusion of tool dependence on reachability** is investigated in the following.

14.3.1 Tool-Dependent Reachability Measure

To incorporate the effects of tools and equipment on the feasibility of robots in performing a given task, we derive the reachability measure of possible robot flange poses. Therefore, firstly, the multitude of theoretically possible robot flange poses to perform the assembly task (visualized as yellow circle on the left of Fig. 14.3) has to be determined. Secondly, the evaluation of the practical reachability of those robot flange poses as a function of the current base position of the robot (visualized as color scale on the right of Fig. 14.3) is performed and expressed in a quantitative measure. The calculated measure depends on the *Reachability Index* of each of the identified theoretical robot flange poses. The reachability measure is defined as the

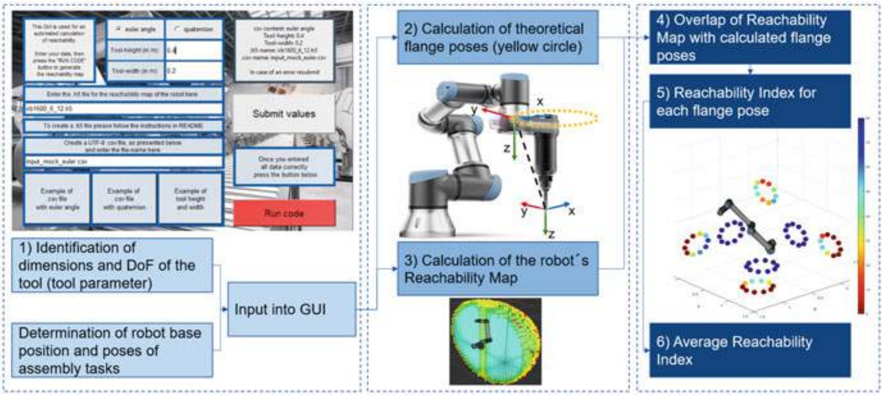

Fig. 14.3 Calculating the overlap of robot flange poses with a *Reachability Map*

arithmetic mean of the *Reachability Index* for all theoretical flange positions of the respective task pose. In detail, the six process steps are as follows:

1. Determination of the dimensions and degrees of freedom (DoF) of the tool or equipment ("tool parameter"),
2. Calculation of the theoretical robot flange poses based on DoFs of the tool and tool center point goal pose,
3. Generation of the robot's *Reachability Map*,
4. Overlap of the flange poses with the *Reachability Map*,
5. Calculation of the *Reachability Index* for each flange pose, and
6. Calculation of the average value of the *Reachability Index*.

To enhance the practicability of the process, a GUI was developed in which the respective parameters can be specified. The calculation runs in the background and outputs a visual representation of the evaluated workspaces as well as the quantitative reachability measure.

The process to determine the tool-dependent reachability measure is validated on a UR10, which is equipped with a screwdriver as a tool. Following Dong and Trinkle (2015), the *Reachability Map* of the UR10 is generated. The set of possible robot flange poses is calculated for a screwdriver with one degree of freedom, resulting in a circular arrangement of robot flange poses, in which the screwdriver's tool center point would reach the goal pose (visualized as yellow circle on the left of Fig. 14.3). Each of the flange poses is assigned to the Euclidean closest value of the *Reachability Map*.

14.3.2 Outlook

Formation planning in assembly stations aims at the capability-based allocation of tasks to resources and the initiation of a spatial formation of all resources. As summarized above, we developed a description model, implemented a capability-based task allocation, and included an evaluation of task executability in the environment of the robot. Pending is the derivation of base placements of the robots in dependence on the executability of the allocated tasks to derive a formation. The goal is to transfer the finalized formation (consisting of allocated assembly poses, robots, and base placements) to the next module of motion planning, as presented in Sect. 14.4.

14.4 Consensus and Coordination in Sensor-Robot Network

Due to their large workspace and high manipulation capabilities, open-chain robotic manipulators with high DoF (e.g., six DoF for static manipulation tasks or nine DoF for mobile manipulation) are commonly used in assembly. Therefore, the *Robot Holon* and its *Sensor Holons* are central parts of the *Resource Layer* of our holarchy introduced in Fig. 14.1. The interaction of these holons with the *Process Holon* of the *Process Layer* controls the automated execution of operation in LMAS.

Taking the previous task allocation and base placement of robots in Sect. 14.3 as an input follows the motion planning of the robot to execute the allocated tasks. Although deciding on the appropriate motion is natural for human workers involved in the assembly process, it can be challenging for automating robotic systems. Robotic systems should be able to adapt their motions to ongoing changes in the assembly, developing a natural behavior, i.e., creating a **safe and predictable environment** for their human "counterparts." For reliable motion planning and motion control algorithms, we must consider the changes of the environment. Robotic manipulators utilized in collaborative environments should be able to employ online motion planning, i.e., the manipulators should be able to quickly react to changes of the environment. This leads to the development of the **real-time-capable response behavior of the systems of a LMAS**.

In this context, powerful algorithms have been developed for various aspects of continuous and discrete planning, for instance, by Biagiotti and Melchiorri (2008), LaValle (2006), and Lindemann and LaValle (2005). Most of these motion planners are developed for robotic systems with low-dimensional configuration spaces, e.g., planar systems, or mobile robotic platforms. Open-chain robotic manipulators, however, are normally of high (generally at least six) DoF, to handle the tasks defined in the six DoFs of the real environments. Thus, the applicability of these algorithms in dynamic environments, such as LMAS, is rather limited.

14.4.1 System Modeling

The main hurdle in developing algorithms that enable the integration of open-chain robotic manipulators in LMAS, i.e., the motion planning algorithms that enable quick responses to changes in the robot's environment, is system modeling. The conventional modeling procedure of the 6D Task space ($\mathcal{T}$-space) of robot manipulators exhibits representation singularities, i.e., the representation of the orientation in some combinations of the EULER angles leads to ambiguities, so that a unique derivation of the initial combination of the angles is not possible, which hinders the planning of a unique path. To enable the motion planning for robot manipulators with online properties, i.e., to react to changes in the environment during planning, it is advisable to use singularity-free modeling approaches for the systems, e.g., the modeling approaches based on LIE theoretic conventions as introduced by Müller (2018) and Lynch and Park (2017) or developed over the ring of dual quaternions by Shahidi et al. (2020). This type of system modeling not only enables a compact and singularity-free modeling of the systems in the $\mathcal{T}$-space of the robotic manipulators but also results in a lower memory footprint for the calculation of the motion.

14.4.2 Motion Planning Algorithms

An optimal system modeling will only partially address the problem of online motion planning for open-chain robotic manipulators. The majority of the motion planning algorithms are either developed in the $\mathcal{C}$-space of the systems or for systems that have similar $\mathcal{C}$-space and $\mathcal{T}$-space, such as non-holonomic mobile robotic systems, like the one presented in LaValle (2006) and Koenig and Likhachev (2005). However, the $\mathcal{C}$-space and the $\mathcal{T}$-space of the robotic manipulators are basically of different cardinalities. Moreover, the forward kinematics function for open-chain robotic manipulators is a non-injective surjective function. These facts are not taken into account when the sampling process for the sampling-based planning algorithms is performed in the $\mathcal{C}$-space of the system as is common in state of the art. Hence, the direct adaptation of the successfully developed algorithms for dynamic environments, e.g., by Koenig and Likhachev (2002), to open-chain robotic manipulators is only possible to a very limited extent. In recent research by Shahidi et al. (2022), we have developed a novel algorithm that combines the information from the $\mathcal{C}$-space and $\mathcal{T}$-space of the open-chain robotic manipulators and prepared an optimal structure of a graph, dubbed *kinematic graph*, to be utilized in the sampling-based planning algorithms. In the proposed algorithm, it is possible to employ the cost and heuristic functions from both spaces and facilitate an optimal motion planning within different aspects. Figure 14.4 illustrates qualitatively different configuration motions generated by the developed motion planner for a simple two DoF mechanism. It can be observed that the motion of the mechanism seems more natural, when the manipulability of the mechanism is considered in the cost and heuristic functions in the planning process. Note that the computation of the heuristics based on the $\mathcal{C}$-space information demands the knowledge of the configuration of the mechanism at the goal posture; hence, the inverse kinematics function should be performed. This can be problematic due to the non-injective surjective behavior of the forward kinematics function, i.e., multiple answer possibilities for the inverse kinematics function. The case where both the cost and heuristic function rely on the $\mathcal{C}$-space information only is presented for demonstration purpose.

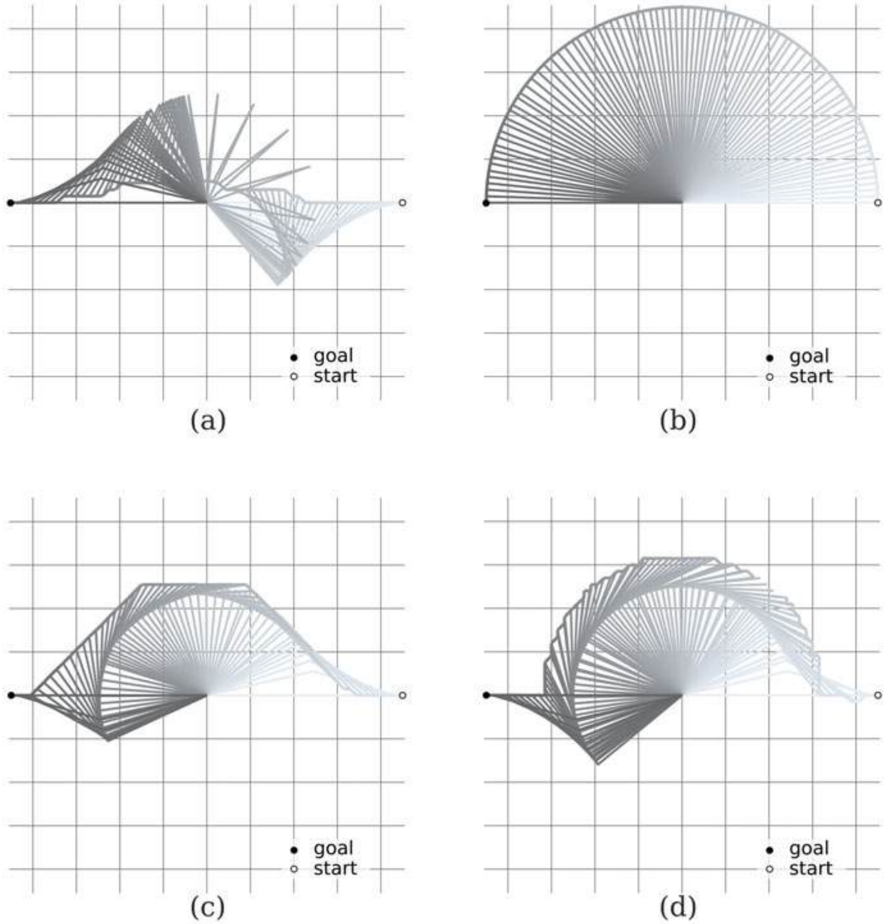

Fig. 14.4 Motion of a two DoF mechanism based on different cost and heuristic functions that are considered in the motion planning problem. The trace of the end-effector of the mechanism and the configuration of the mechanism evolve from light blue to gray. (**a**) cost function: the EUCLIDEAN distance in the $\mathcal{T}$-space; heuristic function: the EUCLIDEAN distance in the $\mathcal{T}$-space. (**b**) cost function: the EUCLIDEAN distance in the $\mathcal{C}$-space; heuristic function: the Euclidean distance in the $\mathcal{C}$-space. (**c**) cost function: the combination of the EUCLIDEAN distance in the $\mathcal{T}$-space and the manipulability of the mechanism; heuristic function: the combination of the EUCLIDEAN distance in the $\mathcal{T}$-space and the manipulability of the mechanism. (**d**) cost function: the combination of the EUCLIDEAN distance in the $\mathcal{C}$-space and the manipulability of the mechanism; heuristic function: the combination of the EUCLIDEAN distance in the $\mathcal{C}$-space and the manipulability of the mechanism

Finally, a fast and time-efficient control scheme can be used to close the loop of system modeling, motion planning, and control and complete the online motion planning for the robotic systems (Shahidi et al., 2020). With the approaches of online motion planning and control in combination with a real-time vision system, the planning of the motion for the robotic systems in assembly can be carried out taking into account high safety and efficiency requirements. However, latencies arising during the compute process can still negatively impact the performance of the control algorithms, e.g., if control signals arrive too late at the robotic manipulators. Reducing the response times is thus a crucial aspect which can be achieved by choosing suitable compute locations close to the system, thus decreasing latency. In the following, we focus on how compute locations *in the network* might help.

14.5 Leveraging Distributed Computing Resources in the Network

Modern shop floors can leverage a multitude of distributed computing resources, ranging from on-premise (edge) deployments to remote cloud services. Choosing the best option from this spectrum critically depends on the concrete process requirements. For the aforementioned robot motion control (cf. Sect. 14.4), e.g., low response times are of highest importance as control signals arriving too late might present a danger to the safe working environment of the human workers. Consequently, motion control algorithms are best executed as close to the controlled robots as possible or even directly on them. However, computational capabilities in edge deployments are typically limited. Additionally, large volumes of information could be leveraged to influence the control decisions, ranging from data of sensors directly mounted on the robots to stationary sensors monitoring the work environments, such as optical sensors (cf. Sect. 14.6). In most cases, processing all available information on the robots themselves is not feasible due to their limited compute capacities. Similarly, sending all sensor information to central computing resources can be prohibitive, either in terms of too high communication latencies or in terms of data volumes that could overload the network. As a middle ground, a growing branch of research explores deploying sensible control functionality onto networking devices which can process high data volumes of several Tbps at sub-millisecond latencies. This *in-network control* can potentially provide the desired real-time-capable response behavior for robot control and LMAS in general.

14.5.1 Laying the Groundwork for In-Network Control

In-Network Computing (INC) has been enabled by latest innovations in networking technologies (Sapio et al., 2017). In particular, networking hardware can now be programmed using domain-specific languages, such as P4 (Bosshart et al., 2014), allowing for highly customizable data processing and filtering directly on the networking hardware. In the context of these advances, the possibility of deploying control functionality into the network has already been studied. For example, we have shown that offloading simple linear-quadratic regulator (LQR) controllers to networking devices can have benefits in settings with higher latencies (Rüth et al., 2018). Similarly, Cesen et al. (2020) show that deploying latency-critical tasks on networking hardware can improve reaction times of robot control scenarios compared to pure remote control. In addition to these direct applications to control tasks, we have focused on providing crucial building blocks for INC applications and control algorithms in general. In particular, we have demonstrated that simple image processing methods (Glebke et al., 2019), data transformation techniques (Kunze et al., 2021a), as well as signal phase detection and dynamic data pre-processing (Kunze et al., 2021b) are possible using INC. These results showcase the potential of INC, further diversifying the distributed computing resource landscape existing today. Thus, INC constitutes one part of our *Technology Layer* (cf. Fig. 14.1).

However, the direct applicability of these approaches to existing architectures, e.g., realistic robot control scenarios using the Robot Operating System (ROS), is questionable: In our work, we mostly rely on the User Datagram Protocol (UDP) and provide custom-tailored solutions, while Cesen et al. implicitly intercept ongoing Transmission Control Protocol (TCP) connections and perform opaque operations in the network that the central controller is not aware of. Whether this behavior is an acceptable practice and how INC should interact with transport protocols in general is still part of ongoing discussions (Kunze et al., 2021c). Similar questions also arise for many of the other related approaches that initially focused on identifying sensible application areas for INC (cf. Hauser et al. 2021). With growing maturity, research on in-network control and INC in general is shifting toward the development of frameworks that allow for the seamless integration into existing architectures, addressing some of the concerns raised above as well as additional criteria that we have collected (Kunze et al., 2022).

14.5.2 Toward Deployable In-Network Control

The fundamental challenge of using INC for control tasks in existing frameworks is the integration into today's transport protocols. These protocols establish end-to-end connectivity between the devices, but typically expect the network to deliver packets without modifications (Kunze et al., 2021c). INC violates this assumption and is thus not directly compatible with many of the connection-oriented transport protocols, such as TCP (Stephens et al., 2021). While connectionless protocols, such as UDP, often allow for the desired changes to the packets, these approaches currently require manually defining the semantics of the INC operations and a corresponding manual adaptation of the application logic. Hence, deployment on larger scales is far from trivial. Consequently, there is a need for general frameworks that define standard interactions with INC functionality and, especially, how this functionality can be included in the transport protocol semantics.

Moving toward this goal, we envision to implement ROS-based control functionality using INC while respecting the semantics of existing transport protocols. In this context, it is important to note that ROS communication by default uses TCP, while a module providing UDP connectivity is not well maintained. Thus, currently, INC-tolerant transport protocols are not yet available. Possible solutions are either using a novel, message-oriented protocol that is specifically designed for use with INC (Stephens et al., 2021) or adapting existing message-oriented protocols, such as UDP or the Stream Control Transmission Protocol (SCTP), for use in ROS with INC. Enabling this critical component for ROS-based communication will be key for deployment-ready robot control scenarios that leverage INC, e.g., for faster image processing (Glebke et al., 2019) to localize the robot in the shop floor.

While this concrete example will likely benefit from the significantly reduced processing times, other components of our overall system are far less latency-sensitive. For example, the aforementioned optical sensors cannot only be used for robot control, but also for monitoring and assuring the quality of assembled or produced components. In these settings, deployments that capitalize on INC are thus not required, and the respective approaches can also be deployed on other compute resources, consequently leveraging higher program complexity, as we will discuss next.

14.6 Trustworthy Vision Solutions Through Interpretable AI

As outlined in Sect. 14.4, resources such as mobile robots need to react appropriately to expected and unexpected events and must therefore understand and interpret their environment in context-aware real time. While Sect. 14.5 concentrates on the infrastructural requirements to take data-driven decisions in time, this section addresses the *Technology Layer* of the underlying holarchy of LMAS (cf. Fig. 14.1) by investigating how to intelligently extract the relevant pieces of information from the image or video data acquired from optical sensor systems.

Vision sensors, such as cameras or triangulation sensors, are often used to acquire a precise digital representation of a resource's proximity or performing a quality control of assembled parts. Analyzing large amounts of images or point clouds and extracting the relevant pieces of information to make decisions is challenging due to the complexity of LMAS scenarios. Deep Learning (DL) promises to solve these obstacles by a rich set of data-driven tools and techniques, many of which were successfully employed in the field of autonomous driving and operation of resources (Grigorescu et al., 2020). These methods, however, usually operate as black box models. For this reason, the underlying criteria of decisions made by these models remain unknown; thus, the inverse direction of assessing the actual properties of the input that caused a certain decision is not comprehensible. This leads to a general level of mistrust in decisions made by DL models and makes them inapplicable for an autonomous operation as required in LMAS.

14.6.1 Interpretable Machine-Learned Features Using Generative Deep Learning

The interpretation and explanation of DL models is an active field of fundamental research in machine learning (Fan et al., 2021; Selvaraju et al., 2017). Current industrial settings mainly use discriminative DL models that assign a decision boundary to a given dataset $\mathcal{X}$ to divide new samples into a set of classes $\mathcal{Y}$. *Generative DL* models approximate the distribution of the data $p_{\mathcal{X}}(x)$ by means of a function $\mathcal{G}_\theta : \mathcal{Z} \rightarrow \mathcal{X}$ that maps from a latent space $\mathcal{Z}$ to observation space $\mathcal{X}$. The function is thereby modeled by a neural network with parameters θ which are inferred during training the model. After training, the generative model can be used to synthesize samples that possess the characteristics of real data samples and present an attempt to improve the interpretation of DL models. The properties of a latent vector $z \in \mathcal{Z}$ and the effect of translations $z' = \alpha z + \beta$, with $z, \beta \in \mathcal{Z}$ and $\alpha \in \mathbb{R}$, can be visualized by generating the corresponding image with the generative model. By this, latent space can be interpreted by means of characteristics of the data.

Style-based Generative Adversarial Networks (GANs) (Goodfellow et al., 2014; Karras et al., 2021) learn disentangled factors of variation $z \in \mathcal{Z}$ allowing for the control of distinct characteristics of synthesized data samples, which leads to a higher level of interpretability of the machine-learned features. By adding a GAN inversion mechanism to the generative model, such as a dedicated encoder network mirroring the generation process as in the Adversarial Latent Autoencoder (ALAE) Framework (Pidhorskyi et al., 2020), real samples can be projected into the interpreted feature space, which allows for the assessment of the characteristics of these embedded samples. Through this procedure, $\mathcal{Z}$ can be used, e.g., to interpret the properties that cause a certain decision by visualizing a corresponding counterfactual example (Lang et al., 2021).

14.6.2 Initial Implementation on a Synthetic Dataset

To investigate whether machine-learned features from generative models can be identified and associated with human-understandable image properties, we created an artificial image dataset containing 10,000 white, centered ellipses on a black background for this study. The ellipses are fully characterized by three quantities: major axis length MA, minor axis length ma, and rotational angle ϕ. An ALAE with a style-based GAN was implemented using Python 3.8.5 and the PyTorch v1.8 framework following the code provided by Pidhorskyi et al. (2020). We have implemented and applied this framework including a more detailed justification for metrology applications in Schmitt et al. (2022). In this study, the model was trained up to a resolution of 32×32 pixels. By sampling random vectors in the disentangled latent space $\mathcal{W}$, images of ellipses can be generated and confirm that the model is able to learn the data manifold (cf. Fig. 14.5 top left). To investigate whether the encoder network maintains the properties of the ellipses, we passed images through the encoder and reconstructed them utilizing the generator (cf. Fig. 14.5 top right). The reconstructed ellipses resemble the properties of the input ellipse, however leading to slightly blurred edges. One possible reason for this behavior might be that style-based GANs (that is used as generator network for ALAE) apply moving average filtering during training, which attenuate high-frequency components in the image. To identify latent variables ξ_i corresponding to properties of the ellipses, we randomly sampled 1000 vectors $z \in \mathcal{Z}$ and applied a principal component analysis

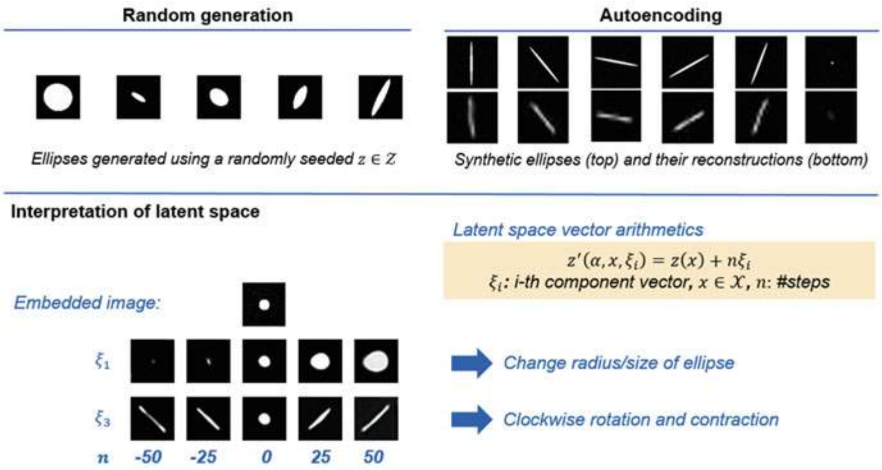

Fig. 14.5 Results of a preliminary toy implementation on a dataset of synthetic ellipses

(PCA) according to the procedure proposed in Härkönen et al. (2020). Figure 14.5 (bottom) depicts the effect of embedding an ellipse into $\mathcal{Z}$ and observing the effect of the two components ξ_1 and ξ_3. The first principal component corresponds to a change of the area of the ellipse, while the third principal component represents a contraction and rotation of the ellipse.

The initial implementation evaluated on the synthetic ellipse dataset indicates that unsupervised methods such as PCA can be used to identify relevant characteristics of the data in the disentangled latent spaces of style-based GANs. As presented in Schmitt et al. (2022), the method is also capable of extracting interesting characteristics from industrial image datasets. These identified characteristics in combination with the generative capabilities can be used in the Internet of Production to support humans, e.g., by providing them with explanatory images for the decision of an autonomous agents, such as those employed in LMAS.

14.7 Multipurpose Input Device for Human-Robot Collaboration

Due to the combination of the growing number of robots in the industry worldwide (International Federation of Robotics (IFR), 2018) and the increasing collaboration between humans and machines (Matheson et al., 2019), the work environment changes: The assembly of the future will be shaped by

1. Robots with high levels of autonomy – enabled by technologies such as presented in Sects. 14.3, 14.4, 14.5, 14.6 – and
2. Human-robot collaboration (HRC) in areas where human work is irreplaceable.

Understanding the behavior of machines – e.g., through explainable AI (cf. Sect. 14.6) – is an important factor for the acceptance of machines in HRC by humans.

Krupitzer et al. (2020) provide an overview of the state of the art of human-machine interfaces (HMI) in the Industry 4.0 domain. Where the workspaces of human and machine are merging, new, more flexible, and **ergonomic operating concepts** for machines are necessary. With the increasing number of (different) machines in combination with their growing range of functions utilized in production, a new generation of input devices is needed that enables operators to control different machines – if necessary also simultaneously. The resulting HMI allows the *Human Holon* (cf. Fig. 14.1) to communicate with other holons of the assembly station, namely, *Robot Holon*, *Sensor Holon*, and *Product Holon*. Applied to the LMAS, such an HMI enables the integration of a human worker: When a station is formed at where a worker is to perform tasks, all robots and tools can be accessed ergonomically and seamlessly without media discontinuity. The overarching research question to be answered is how an HMI can be designed to allow a human to operate several different types of machines focusing on

1. Usability,
2. Workload, and
3. Safety.

14.7.1 Application, Implementation, and Result

The assembly of a truck is chosen as an application scenario: An overhead crane carries the drive train and an Autonomous Guided Vehicle (AGV) provides the vehicle frame onto which the drive train is to be mounted. A robot arm assists with the positioning. Currently, each machine is operated by one worker and an additional worker supervises, secures, and instructs. For *Future Assembly* a multipurpose input device shall be developed, enabling a single worker to handle all listed tasks.

There are two perspectives to this problem:

1. From the *technical* point of view, the components to be assembled are large and heavy and move dynamically. Therefore, the handling is nontrivial.
2. From an *ergonomic* point of view, time pressure as well as the rapid and frequent changes between different parallel tasks (multitasking) is exhausting for humans. This leads to fatigue, which can cause errors. The challenge is therefore to maintain situational awareness and to keep – especially the cognitive – workload in an optimal range.

The goal is to develop an input device that enables a single operator to control these different machines (overhead crane, AGV, and robotic arm) without or with little training. Another aspect is to use available data to assist the operator in

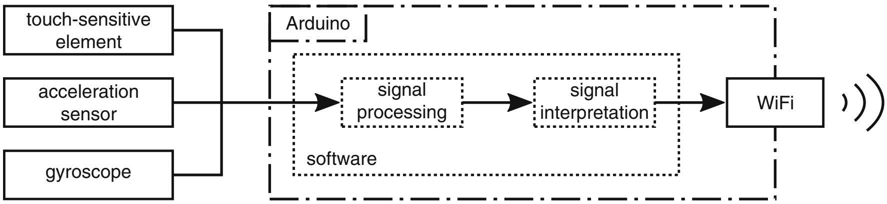

Fig. 14.6 Schematic design of the multipurpose input device

performing the task and to provide information to the operator. This includes consideration of not only the technical but also the human factor.

VDI 2221 was chosen as the design methodology. The detailed design procedure is described in Baier et al. (2022).

Figure 14.6 shows schematically how the input device for **simultaneously controlling different machines** is designed. A prototype of the input device is in the making: The design features a lightweight and wireless wearable. This allows the operator to move freely during the process and relative to the machines, as a distinct advantage during HRC. The input device functions as HMI as a dedicated intermediate layer between the human and machine domains. Mechanical inputs – in the form of movements or button presses – are received from the operator, are processed on the device, and are sent to the control unit via Wi-Fi. This is implemented in the form of a 3-axis acceleration sensor and a 3-axis gyroscope, which enables the device to control 6 DoF. In addition, there is a touch-sensitive element on each finger.

Interaction concept Few commands are sufficient for operation, which is why the interaction concept provides for comparatively simple control with hand movements and gestures. A decisive factor for the safety of the control system is error robustness, so that unintentional inputs are not implemented or at least do not cause any damage. Thus, inputs can only be made when a certain touch element is touched, which also doubles as a dead man's switch. As mentioned before, inputs are evaluated depending on the context and interpreted as commands or discarded. For this purpose, the input device first detects the movements and then processes these signals into inputs. Depending on the machine currently being controlled, valid commands are recognized from these inputs by matching the recognized pattern with the command set stored for the machine in advance. In addition, assistance systems based on the digital shadow are designed to increase safety.

14.7.2 Outlook

Simulation studies First, pre-studies will be conducted in the simulator to determine optimal settings for the device. This will be followed by further simulation studies of usability and performance for abstract tasks, and the simulated use case will be investigated. The outcomes will be validated by a physical laboratory study on an AGV with a manipulator.

Use of the digital shadow To keep the (cognitive) workload for the operator low, an assistance system will be created to support the operator by automating tasks that do not require human intervention. Digital shadows of previous assembly operations will be used as a source of information. For example, an automated system could automatically follow previous trajectories in noncritical areas to free the operator from this task or, as a safety measure, compare the current trajectory with previous trajectories and warn the operator if the deviation is too large. Behavior trees are to be used as data structure for this modeling, since they can represent process steps both discretely and simultaneously.

Section 14.8 is focused on the support of the user by the system as well. All relevant information is presented to the user through an interface. This information is collected and processed from various sources using an ontology.

14.8 Ontology-Based Knowledge Management in Process Configuration

Another challenge of human machine collaboration is creating a unified understanding of the existing relationships of process parameters. In complex assembly systems, like LMAS, where the number of process parameters is high, there is no trivial solution for understanding process relationships and dependencies. Accounting for this, the Model Composition domain in the *Technology Layer* of the Future Assembly Holarchy (cf. Fig. 14.1) can be achieved by ontology-based knowledge management. To demonstrate the benefit of knowledge-based assistance systems in LMAS, we modeled the influence parameters of the side window assembly in automotive body assembly, where industrial robots are being used for adhesive application. The quality of the application is crucial for the stability of the subsequent bonding and depends on a number of adhesive and process parameters, such as flowability, bead cross-section, travel, and adhesive exit speed. Correct adjustment of the process parameters requires precise knowledge of the complex relationships between the process and adhesive parameters and their effect on upstream and downstream process steps. Thus, it is difficult for the operator to find solutions for suitable control parameters in the event of a process change.

Semantic technologies offer great potential for solving two main challenges of process parameter configuration (Lipp and Schilling, 2020; Sahlab et al., 2021): on the one hand, to create a complete system knowledge base including expert knowledge and, on the other hand, to assist in the search for configuration solutions. Due to a graph structure consisting of a large number of connected nodes or data points, ontologies enable a more flexible modeling of existing data relationships than tabular databases or hierarchical class diagrams. The set of nodes can be expanded as desired, which allows the networking of individual data domains to be modeled and the integration of existing expert knowledge. Furthermore, concepts of graph theory are particularly well-suited for solving optimization problems in which pairs of objects are related (Dengel, 2012). Moreover, ontologies can be based on already existing data management systems, so that no complete remodeling of existing data is necessary (ontology-based data access, OBDA).

14.8.1 Concept and Implementation

An ontology-based configuration tool can consolidate already existing product and process information, expand it with expert knowledge, and uncover new knowledge connections by creating new relationships between the data points of distributed process data resources such as data models and control units. The generated knowledge base can be used as the basis for assistance solutions to optimize process configuration and, thus, shorten the planning and configuration time. This contribution presents an approach to develop an assistance system for knowledge-based control process configuration.

Figure 14.7 shows the intended approach for designing an assistance system for knowledge-based control process configuration. An essential aspect of the approach is the conception of the knowledge management system.

Based on the specific process requirement description, we carry out the model specification of the knowledge management system (A). For this purpose, we analyze existing approaches for semantic modeling of robot-based processes, such

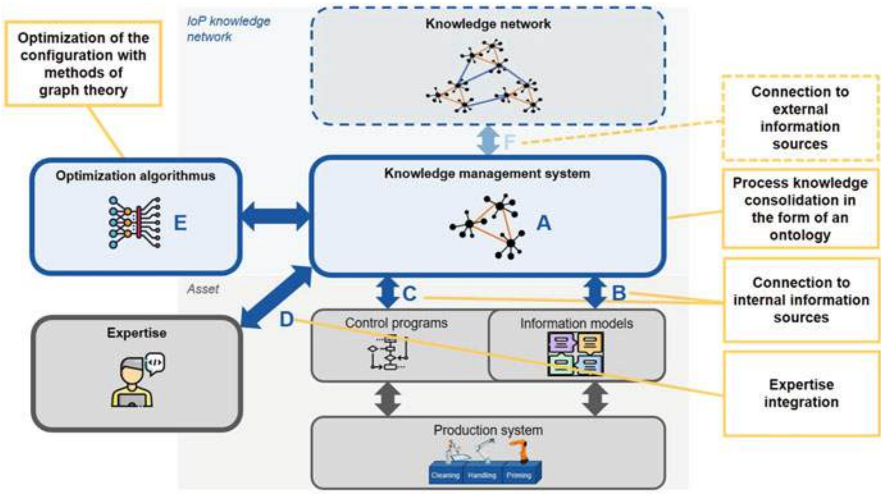

Fig. 14.7 Concept of an assistance system for knowledge-based control process configuration

as CORA (Core Ontology for Robotics and Automation), MARCO (Manufacturing Resource Capability Ontology), and SUMO (Suggested Upper Merged Ontology) and use them as a system basis (Brecher et al., 2021; Prestes, 2013). Subsequently, we examine the connection possibilities of the system to process-internal data sources (B and C). Of great importance is the evaluation of the integration possibilities of the developed process interface with the OPC UA information models of the assembly process (B). OPC UA is considered, because it is one of the most widespread communication protocols in production technology. Ontologies based on the Web Ontology Language (OWL) standard can provide formal semantics and better search functionality compared to OPC UA models (Schiekofer and Weyrich, 2019); thus, we consider a transformation of OPC UA information models to the ontology-based knowledge management system. Subsequently, we examine the connection of the knowledge management system to already existing control logic or process chains (C). Furthermore, the integration of existing expert knowledge in the form of machine-readable, interpretable metadata into knowledge management system is in the focus of consideration (D). Finally, we conceive a possibility for integrating the knowledge management system into a future overarching semantic network of the IoP (F). This is achieved by designing of a communication possibility between ontologies of different abstraction levels through a bridge concept between domain and application ontologies.

The aggregation of data from process control, information models, and experience-based knowledge across assembly systems opens up new potential for optimizing assembly process control, which could not be exploited until now due to the lack of networking of relevant data sources and semantic expressiveness of existing information. In particular, the use of methods of graph theory and operations research (OR) opens up new possibilities. Therefore, different methods can be applied to the use case of robot-based adhesive process described above, such as, e.g., mixed-integer linear optimisation (MILP) and machine learning methods (E).

Based on the described architecture, we created a system that simplifies the solution search for suitable industrial parameters for a programmer. The system initially includes the following functionalities: suggestions for time optimization, help in changing the adhesive to be used, and troubleshooting. The functionality of the assistance system will be briefly presented using the example of time optimization. The ontology based on CORA concepts is used as a basis for finding the data, which reveals their interrelationships, e.g., those between the individual process variables such as pump output and adhesive density. Real process data such as trajectory values are saved, filtered, and stored in an SQL database. The ontology can access the database of actual values using the OBDA approach (R2RML), turning it into a knowledge graph. The resulting knowledge graph is then used as a guide for the optimization algorithm (parallel machine scheduling), which detects optimization potential in terms of process time. If optimization potential exists, the assistance system suggests the process variables that need to be adjusted to achieve this potential, e.g., the speed of the robot.

14.8.2 Summary and Outlook

In summary, semantic technologies, such as ontologies, represent a promising approach to knowledge-based assistance for process configuration of robot-based assembly processes, which can integrate existing expert knowledge and transfer already existing knowledge sources such as information models and flow logic structures. In the further course of the research, we will identify and evaluate further optimization algorithms describing the assistance performance of the system. Subsequently, we will use these algorithms to expand the assistance performance of the developed system with additional functionalities. Moreover, we will create methodologies for an efficient transformation of common data exchange formats to a knowledge graph format.

14.9 Conclusion

We present services and concepts for modular control enhancing the future operation of lineless, mobile assembly, based on a previously developed system architecture. We contribute the following research focal points through applying and extending principles of the Internet of Production (IoP) in lineless mobile assembly systems (LMAS):

Closing the gap between high-level scheduling and low-level robotics control, we introduce measures for the modular formation planning for mobile robots in assembly stations. Based on the resulting formation, consisting of robot base placement and task allocation, the robot motion planning to execute those tasks is carried out. Firstly, we have developed a compact and representational singularity-free modeling for the robotic manipulators that enables the use of fast motion control strategies. Secondly, we have developed the structure of a novel graph specifically designed for open-chain robotic manipulators to enable the effective implementation of the sampling-based scheduling algorithms using heuristic functions. There is a lot of potential in previously unused networking resources that can now be leveraged using INC, to, e.g., compute the motion planning. Their application to existing communication scenarios, however, requires new transport protocol solutions that do not break when subject to INC. Similarly, novel methods based on generative deep learning might help to visualize and explain the decisions of neural networks and, thus, increase the level of autonomy of resources in LMAS. In work systems of future industrial assembly, human work will take place in the context of Human-robot collaboration. We have presented an approach to enhance safety, ergonomics, and workload reduction in HRC based on a HMI that allows different machines to be controlled flexibly and as needed. We introduced semantic technologies (ontologies) as a promising approach for knowledge-based assistance solutions to automatically configure robot-based assembly processes.

In future work, we plan to deepen the knowledge of the research focal points as well as further integrate research labs, engineering, and production sites into a combined demonstrator, following the principle of the **World Wide Lab**.

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Part V

Production Management

Methods and Limits of Data-Based Decision Support in Production Management 15

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Abstract

The volatility of today's markets is constantly rising due to, i.e., the rapid emergence of new and innovative competitors, changing government policies, and unknown market acceptance. This affects both short-term and long-term production management. While short-term production management must deal with a higher time sensitivity of decisions, long-term production management must deal with an increasing level of uncertainty in decisions. Thus, to stay competitive in the future, short-term production management must especially increase the implementation speed of decision, whereas long-term production management focuses on the improvement of decision quality in uncertain environments. Therefore, the Internet of Production (IoP) develops data-based decision support methods for both short-term and long-term production management, which are presented in this chapter. For short-term production management, data-based decision support methods are presented for quality control loops, production planning and control, as well as production system configuration. For long-term production management, methods are presented for factory planning, global supply chain management, and production network planning.

15.1 Introduction

More and more aspects of our lives are consciously or unconsciously captured and stored by data. This is especially true in production. According to IBM, a modern factory generates 1 TB of data per day (IBM 2022). At the same time, data modeling methods, for example, based on artificial intelligence, are becoming increasingly powerful. The combination of both aspects makes it obvious to use data-driven modeling methods in production in order to support decision-making processes with "what-if" analyses (acatech 2021).

The applied decision support methods depend on the level of production management, which can generally be divided into two categories: *short-term and long-term production management (cf.* Figure 15.1*). Short-term production management* includes all operational processes on a machine and shop floor level and must especially deal with a high volatility of the environment.

Long-term production management includes processes on the level of the whole factory as well as a worldwide production network with several locations and must mainly conquer the high uncertainty of the environment. The different expressions of volatility and uncertainty influence the decision support methods being applied in short- and long-term production management (Ivanov 2018).

To quickly compensate for disturbances within the production system, time sensitiveness of decisions is decisive, which is why the decision support methods in short-term production management aim to significantly increase decision and implementation speed. To deal with the high level of uncertainty within the production system, decision support methods in long-term production management aim to maximize decision quality.

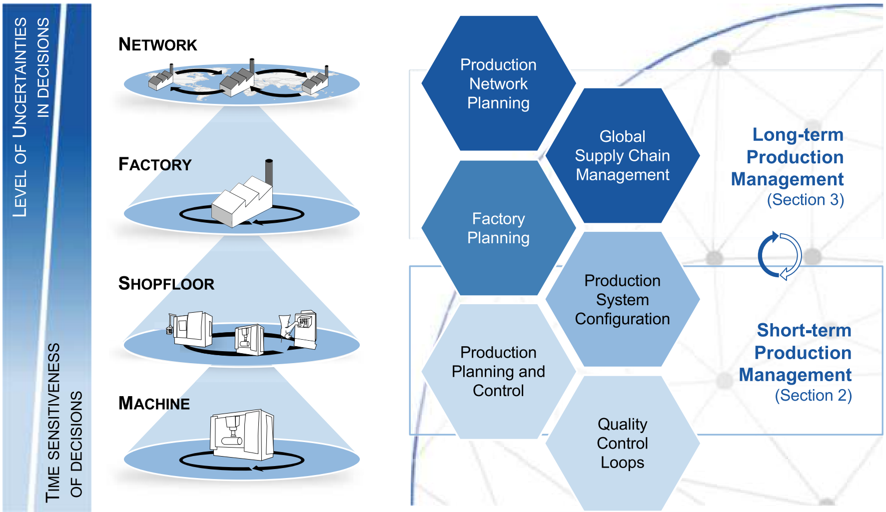

Fig. 15.1 Time sensitivity and uncertainty of decisions in short-term and long-term production management

This chapter presents data-based methods to support decision-making in production management while dealing with time sensitiveness and uncertainty. These methods are developed on the basis of six use cases, as shown in Fig. 15.1. Thereby, decision support is realized with so-called applications (apps) focusing on the information need of decision-makers in production. The following sections present these applications. Section 15.2 focuses on short-term production and thus on increasing decision and implementation speed. Section 15.3 focuses on long-term production and how to increase decision quality.

15.2 Increasing Decision and Implementation Speed in Short-Term Production Management

The volatility of today's markets is constantly rising due to the rapid emergence of new and innovative competitors, changing government policies, as well as unknown market acceptance – to only mention some factors. Therefore, production is more and more characterized by shorter product lifecycles, increased individualization, and disruptive technological changes (Schlegel et al. 2018). The tasks of short-term production management thereby include, i.e., occupancy planning, resource monitoring, quality control, and order scheduling. Thus, short-term production management must secure that change requests or disruptions on the shop floor (e.g., machine failure) are compensated via appropriate control loops. A quick response to changing circumstances and requirements is crucial to achieving corporate goals. Consequently, the ability of short-term production management to carry out process adjustments efficiently is of particular importance (Petschow et al. 2014).

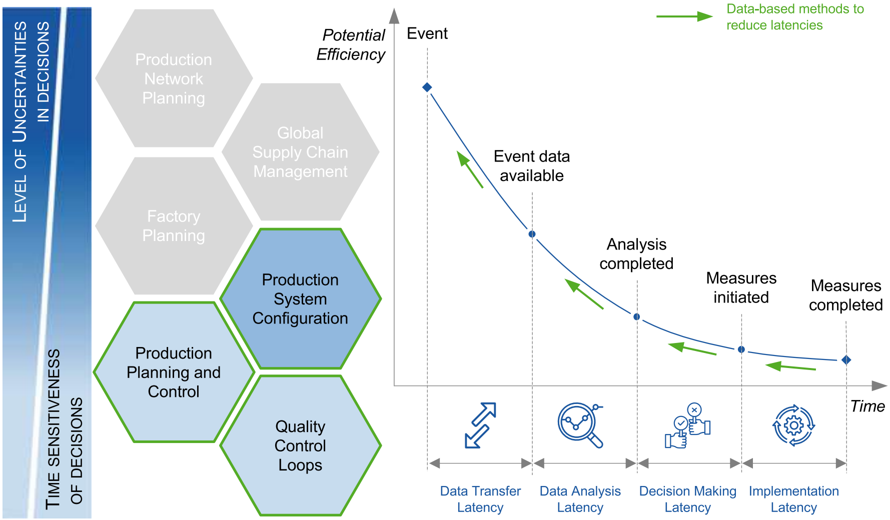

Fig. 15.2 Potential efficiency enhancement by reducing latencies in short-term production management

A key requirement for efficient process adjustments is the reduction of the *overall latency* between the occurrence of an event and the implementation of the derived corrective measures. The lower the overall latency, the higher the value creation of production*, as shown in* Fig. 15.2 (Zur Muehlen and Shapiro 2015; Kiesel 2022). *Overall latency is composed of four delay times: data transfer latency, data analysis latency, decision-making latency, and implementation latency. Data transfer latency refers to the timespan between the occurrence of the event and the moment when data is available for analysis. Data analysis latency is the time of initiating the analysis, packaging its results, and delivering them to the appropriate system. Decision-making latency is the period the system records this information and takes a decision. Implementation latency describes the time between the decision and the execution of the corresponding measure* (Hackathorn 2002; Kemper et al. 2010; Sejdic 2019). *Thus, to pursue the goal of overall latency reduction, the four presented sub-latencies must be reduced.*

In order to compensate disturbances within the production system as well as to implement changes with the minimum latency possible, the concept of *self-learning production systems* is further developed within the *Internet of Production* (IoP) (Brecher et al. 2017). Within this concept, the availability of real-time shop floor data and machine learning algorithms enables process models to learn from historic process data. This in turn enables the prediction of product quality as well as the adaption of production processes accordingly (Lee et al. 2014). To further develop the concept of self-learning production systems, the IoP pursues three main objectives. First, IoP *develops data-driven methods* (e.g., in the field of process mining) that enable self-learning production systems to learn from historic process data and events and make autonomous decisions (van der Aalst et al. 2020). Second, IoP drastically *minimizes data and analysis latencies* through the integration of continuous cross-domain data access and the development and combination of diagnostic, predictive, and prescriptive analytics models. Third, IoP *reduces decision and implementation latencies* by means of an appropriate collaboration of autonomous processes and model-based decision support as well as the implementation of suitable measures in the production system.

With these three objectives, IoP *increases productivity* by reducing the impact of volatile environments on a steady production system. IoP furthermore *masters quick change requests* by decreasing the period of time which is required to bring the production system back into a steady state after process adjustments.

To better understand both the objectives of IoP and their impact on short-term production management, three applications are presented in the following. Table 15.1 shows their overall goal and their contribution regarding IoP's purpose.

15.2.1 Predictive Quality (Quality Control Loops)

Manufacturing processes have become significantly more complex in the past years due to the ongoing digitalization and interconnection of systems. Early defect detection in interlinked production steps offers the chance to reject affected parts at an early stage of the production process so that costs and efforts for dispensable further processing can be avoided.

Within the IoP, early defect detection is realized by *predictive defect models*. It enables companies to identify problems in process and product quality at an early stage of production by providing the employees with the information they need

Table 15.1 Exemplary applications for short-term production management and their purpose within the IoP

Application (use case)	Application goal	Data-driven method development	Data and analysis latency reduction	Decision and implementation latency reduction
Predictive Quality (Quality Control Loops)	Prediction of defect occurrence in production in early stages based on machine and inspection data	x	x	
Short-Term Production Planning and Control	Optimization of production planning and control using feedback data	x		x
Parameter Prediction (Production System Configuration)	Prediction of machine settings based on specific input data	x		x

to enable data-driven decision support via the application. The models consist of machine and inspection data being interlinked with the process variables that have an influence on defect occurrence.

To develop the predictive defect models coping with the requirements of time sensitiveness of decisions, a flexible process-independent meta-model for production data is developed. This model is the basis for the development of data-driven methods. Based on the context provided by the meta-model, automated machine learning (AutoML) methods for pre-processing and analysis of production data are developed. By automating the ML pipeline, AutoML significantly reduces data and analysis latencies (Schmitt et al. 2021).

15.2.2 Short-Term Production Planning and Control

Production planning and control (PPC) is a highly complex task in job shop production. Companies often struggle an economically beneficial operation strategy in the polylemma of short lead times, low working capital, high utilization, and high adherence to delivery dates. To tackle this polylemma, IoP uses *feedback data* for an optimization of PPC tasks (Schuh et al. 2020).

Therefore, IoP focuses on the development of a *reinforcement learning agent* that uses realistic simulation models of a job shop production for learning and optimizing the task of order release. The simulation model allows an *instant reaction to production disturbances* via order rescheduling, rerouting, and changing of dispatching rules. Thus, considering current production goals, production utilizations are aligned and optimized. The simulation model is generalized over different types of production (e.g., mass customization, craft production, batch production) using transfer learning.

Besides the development of data-driven methods using reinforcement and transfer learning, the app especially enables a reduction of decision and implementation latencies by an autonomous decision preparation based on digital shadows.

15.2.3 Parameter Prediction (Production System Configuration)

In several industries, e.g., the textile industry and plastics production, to date, manual process and machine adjustments are the norms rather than the exception. Thereby, the correct setting of the machine depends on many different parameters and often requires knowledge of an experienced engineer (Müller et al. 2023). To become less dependent on expert knowledge of these engineers and shorten the machine setting duration, the goal of this app is to *predict machine settings* based on specific process data, especially quality parameters.

To do so, a holistic machine learning model is created within the IoP. It is based on *reverse neural networks* (*RNN*). Based on historical or synthetically generated data, the RNN identifies correlations between process parameters and part quality and then calculates process parameters that can be used to produce the desired component with the required properties. This facilitates the induction of new employees in industries dependent on expert knowledge and at the same time objectifies existing domain knowledge. Furthermore, a prioritization between the target parameters of a production system is provided. If, for example, energy consumption is a priority and fast processing is negligible, these specifications can be implemented as an optimization problem and adapted recommendations issued (Müller et al. 2022). Besides the development of predictive models, this app increases the decision as well as implementation speed in production, as parameters are objective and no further decision is required by the machine operator.

15.3 Decision Quality Enhancement in Long-Term Production Management

Long-term production management considers the entire supply chain network and the internal production network. The main goals of long-term production management are cost reduction, flexible production structures, resilience, and sustainability (Lanza et al. 2019). Long-term production management thereby determines the future production structure and consequently has a high impact on the long-term competitiveness. Since long-term decisions often require substantial resources, may be irreversible, and define an organization's direction for years to come, the *decision quality* is of particular importance. Thus, over the last years, data-based decision support systems have been identified as an opportunity to support decision-making processes (Tiwari et al. 2018).

However, achieving a high decision quality through data-based decision support is very difficult, since decisions in long-term production management occur uniquely and infrequent and are subject to a high degree of uncertainty. This uncertainty often results from different and unreliable internal and information sources, such as sales forecasts or market demands (Lanza et al. 2019). In addition, new production platform models require a new degree of openness between market players, which lead to shifting property rights and decision responsibilities and hence a new dimension of uncertainty. While increasing openness can increase value creation, it might be a risk to control value capture (Schuh et al. 2018).

Thus, the main lever to increase decision quality in long-term production management is the reduction of uncertainty in decision situations. Within the IoP, we thereby distinguish between five types of uncertainties occurring in between the need for a decision and its final implementation, as summarized in Fig. 15.3. *Action uncertainty* describes whether the event requiring a decision will occur at all. *Scope uncertainty* is the uncertainty about the environment the decision will affect (Welsh and Sawyer 2010). *Data quality uncertainty* includes the uncertainty of trustworthiness and reliability of the available internal and external data. *Prediction uncertainty* refers to the variability in prediction due to plausible alternative input values (Tavazza et al. 2021). *Decision uncertainty* refers to the variability in decision implementation due to different decision alternatives. *Thus, to increase decision quality, these sub-uncertainties must be decreased.*

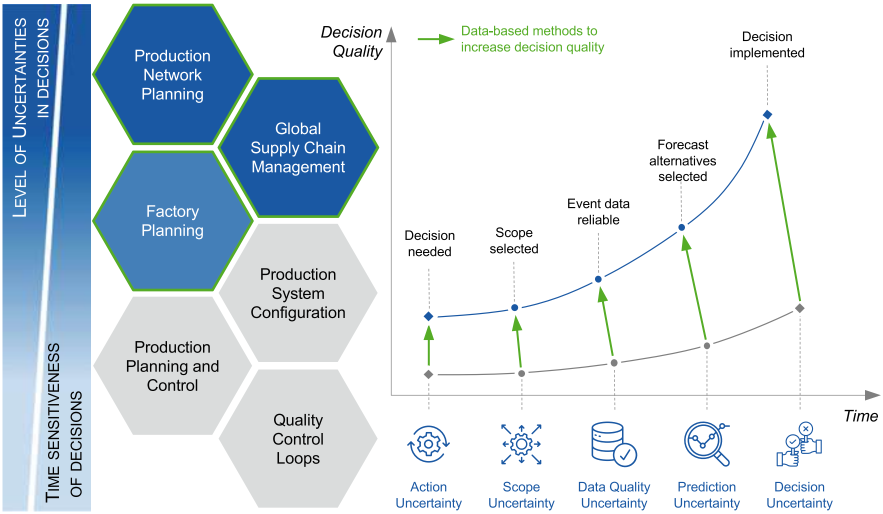

Fig. 15.3 Potential of decision quality enhancement in long-term production management

Therefore, IoP's vision is to improve decision quality by supporting the decision-maker in the proactive design and improvement of production structures in uncertain business environments through *intelligent decision methods and the respective autonomous algorithms*. To realize this vision, IoP pursues three main objectives. First, *adjustment requirements in production structures* are proactively identified by continuously monitoring relevant events in production, product development, and usage. Second, *intelligent methods for an autonomous decision preparation* are developed based on digital shadows. Third, IoP analyzes how the decision-maker can be supported by a comprehensive *suggestion of alternative courses of action* and the assessment of their impact on strategic targets.

With these objectives, IoP delivers *higher transparency and trust* over decision needs, influencing factors and uncertainties as well as the impact of domains like product development and usage. IoP thus enables to continuously monitor and adapt the long-term targets of production. Furthermore, IoP allows a *new way of strategic decision-making* by autonomous decision preparation, analysis, and support. This enables decision-makers to focus on the value-adding part of long-term decisions in designing future production structures.

To better understand both the objectives of IoP and their impact on long-term production management, three applications are presented in the following. Table 15.2 shows their overall goal and their contribution regarding IoP's purpose.

Table 15.2 Exemplary applications for long-term production management and their purpose within the IoP

Application (use case)	Application goal	Proactive identification of adjustment requirements	Methods for an autonomous decision preparation	Suggestion of alternative courses of action
Proactive Factory Planning	Risk-optimized decisions of greenfield factory planning to limit and improve solution space	x	x	
Supply Chain Cockpit – Master Data Quality Improvement (MDQI)	Enhancing data quality in ERP systems to improve quality of databased decisions in procurement	x		x
Footprint Design	Evaluation and improvement of the sustainability characteristics of a global production network	x		x

15.3.1 Proactive Factory Planning

Factory planning projects often fail to comply with time and budget restrictions and thus expose enterprises to a variety of risks. Especially the planning of greenfield factories with an almost infinite solution space – thus many uncertainties – entails the risk of wrong decisions during the planning process. Studies identified information management to lie at the root of this problem, as the information in the planning process are often interconnected and must therefore be managed suitable methods to ameliorate factory planning outcomes. Otherwise, the interconnection leads to even higher uncertainties, which affects the transparency of decision and probably reduces decision quality (Burggräf et al. 2021; Herrmann et al. 2020).

To reduce these risks, risk management must be part of the factory planning process. Risk management aims to identify, assess, and prioritize individual risks of information so that appropriate decisions and actions can be taken. However, standardized methods are not implemented in factory planning yet (Burggräf et al. 2021). Therefore, IoP develops a new risk management method for factory planning. Especially the scope uncertainty (cf. Figure 15.3) shall be reduced by this methodology.

The risk management approach bases on *fuzzy logic methods*. Fuzzy methods allow to model and calculate decision-making deficits and uncertainty of different stakeholders (Bellman and Zadeh 1970). Thus, in the factory planning process, fuzzy logic approaches can be used to make information uncertainties measurable.

Where otherwise only subjective estimates can be obtained, fuzzy logic can contribute to capture information for factory planning scenarios transparently, objectively, and quantitatively (Burggräf et al. 2021).

This objective quantification reduces the uncertainties and thus increases the decision quality in factory planning. Furthermore, fuzzy logic-based risk assessment enables an autonomous decision preparation. It also allows a proactive planning process as risky planning steps are known in early stages of the planning process and can thus be prevented from the beginning.

15.3.2 Supply Chain Cockpit – Master Data Quality Improvement

As past disruptions of the supply chain, e.g., COVID-19 or the blockage of the Suez Canal, have demonstrated, their impact on the procurement side is highly critical. Procurement is responsible for organizing and ensuring the supply of external material and parts that are required for internal processes. Thus, forward-looking procurement planning which is prepared for disruptions is key for production companies (Linnartz et al. 2022).

Thereby, procurement planning is often realized within an ERP system and requires data from various existing and potential suppliers. Data quality thereby affects decision quality significantly. Due to its various sources, data of procurement often lacks quality (Ge and Helfert 2013). Therefore, the IoP developed an app to practically identify, prioritize, and take measures against poor data quality.

This app thereby executes two main tasks: First, it identifies critical data quality problems within the master data of the ERP. Second, based on the identified lacks, the app derives recommended actions and different alternatives to improve data quality. This way, the app enhances trustworthiness and transparency of the data on which procurement decisions rely on. It furthermore proactively identifies adaptation needs in master data quality and recommends alternative courses of action toward improvement. This way, it contributes to an enhancement of the decision quality within long-term production management.

15.3.3 Footprint Design (Production Network Planning)

Sustainability of global production networks is critical. While still being efficient and profitable, production companies must secure sustainability of its network (Alexander 2020). Therefore, global production networks should be continuously evaluated and improved regarding their sustainability characteristics. To do so, IoP develops the *Footprint Design App*, which is designed for production network planners to proactively identify adaptation needs in network design regarding sustainability before the design decision of a network configuration.

The core of this app is a data model to combining production network elements with sustainability characteristics and attributes. This model is fed with data from existing production networks, internal company data, and data from external sources such as LCA databases and transport information. This data is then related to the sustainable characteristics and attributes. This way, the app allows an optimization of global production network footprint.

Decision quality is thereby enhanced in several ways. First, by continuously updating the database and reconfiguring the network, data quality increases, and overall uncertainty decreases. Second, by proactively identifying adjustment requirements as well as suggesting alternatives of network design, the scope of the decision is narrowed down for the production network planner, which again reduces uncertainties.

15.4 Conclusion

Data-driven modeling methods in production to support decision-making processes with "what-if" analyses are of high importance for future production management. Therefore, the IoP develops apps for decision-makers in production to support the decision-making process.

In short-term production management, they support reduction of latencies in the decision process and therefore a faster implementation of decisions, as it was illustrated by the three apps "Predictive Quality," "Short-Term Production Planning and Control," and "Parameter Prediction." Thereby, it was shown that data-driven decision support increases productivity as the impact of volatile environments is reduced. Additionally, quick change requests can be mastered in a much shorter time.

In long-term production management, data-based decision support reduces uncertainties and thus increases decision quality, as it was illustrated by the three apps "Proactive Factory Planning," "Supply Chain Cockpit – Master Data Quality Improvement," and "Footprint Design." Here, decision support increases transparency and trust of decisions. It furthermore allows new ways of strategic decision-making by autonomous decision preparation, analysis, and support.

This way, IoP secures that business goals are reached and market needs are met by improving the decision quality and implementation speed in long-term and short-term production management.

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Managing Growing Uncertainties in Long-Term Production Management

16

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Abstract

Long-term production management defines the future production structure and ensures the long-term competitiveness. Companies around the world currently have to deal with the challenge of making decisions in an uncertain and rapidly changing environment. The quality of decision-making suffers from the rapidly changing global market requirements and the uniqueness and infrequency with which decisions are made. Since decisions in long-term production management can rarely be reversed and are associated with high costs, an increase in decision quality is urgently needed. To this end, four different applications are presented in the following, which support the decision process by increasing decision quality and make uncertainty manageable. For each of the applications presented, a separate digital shadow was built with the objective of being able to make better decisions from existing data from production and the environment. In addition, a linking of the applications is being pursued:

The *Best Practice Sharing App* creates transparency about existing production knowledge through the data-based identification of comparable production processes in the production network and helps to share best practices between sites. With the *Supply Chain Cockpit*, resilience can be increased through a data-based design of the procurement strategy that enables to manage disruptions. By adapting the procurement strategy for example by choosing suppliers at different locations the impact of disruptions can be reduced. While the *Supply Chain Cockpit* focuses on the strategy and decisions that affect the external partners (e.g., suppliers), the *Data-Driven Site Selection* concentrates on determining the sites of the company-internal global production network by creating transparency in the decision process of site selections. Different external data from various sources are analyzed and visualized in an appropriate way to support the decision

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process. Finally, the issue of sustainability is also crucial for successful long-term production management. Thus, the *Sustainable Footprint Design App* presents an approach that takes into account key sustainability indicators for network design.

16.1 Introduction

Production management faces a variety of challenges. Increasing uncertainty combined with growing complexity hinders decision-making and reliable planning. However, shorter product life cycles and disruptive changes require rapid adaptation to change. The benefit of the Internet of Production for production management is to provide data-driven decision support on all levels of managing production in dynamic company environments (Schuh et al. 2019a). Long-term production management sets the future production structure and determines long-term competitiveness. Due to rapidly changing global market requirements and the uniqueness and infrequency of the decisions to be made, it is difficult to achieve a high decision quality (Lanza et al. 2019). However, these decisions in long-term production management are associated with significant costs and can hardly be reversed (Balderjahn 2000). Therefore, the aim of this research work is to improve decision quality despite uncertainty through data-driven decision support. The use of historical data from the company and its environment is combined with appropriate analysis and methods. Decisions in long-term production management are always dependent on the knowledge and experience of the management, so that the interactivity and usability of the data-driven decision supports plays a decisive role in practice (Schuh et al. 2019b).

The data-driven decision support tools are developed for specific tasks and challenges in long-term production management. The *Best Practice Sharing* application aims to facilitate knowledge transfer across sites. In this way, production sites can learn from each other and adapt more agilely to changes. The *Supply Chain Cockpit* can be used to increase resilience through a data-driven design of the procurement strategy to persist in times of disruption. Data from company's internal business application systems like orders and material master data from an ERP system are used to characterize a company's procurement strategy. The approach also explores how improving data quality can drive such data-driven decisions, since the quality of the data included is critical. In the application *Data-driven Site Selection*, the complex process of site selection can be improved in terms of decision quality by using external data such as quantitative and qualitative data from macroeconomics, microeconomics, political economy, foreign trade, and foreign direct investment. A corresponding procedure as well as extensive databases are presented and applied. Further, the growing importance of sustainability is considered in the application *Sustainable Footprint Design*. By means of a software solution, existing cost-based approaches are supplemented by sustainability parameters.

The practical realization of the described decision support tools takes place through the development of a Production Control Center for long-term production

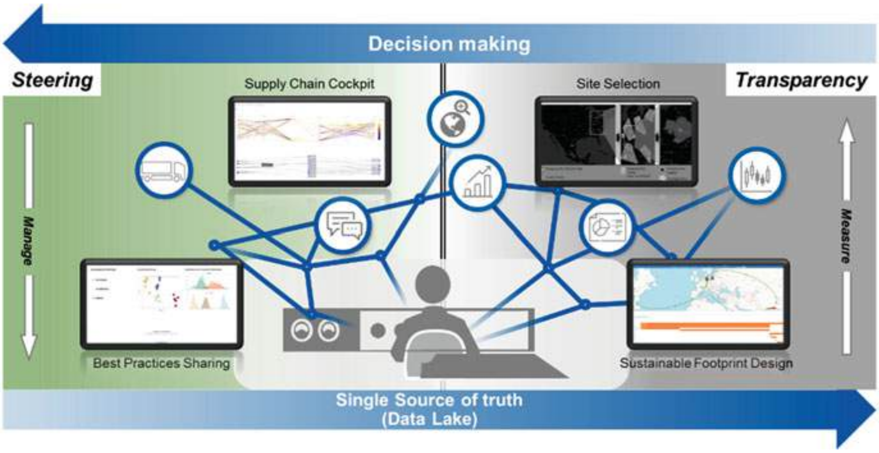

Fig. 16.1 Production Control Center for long-term production management

management. Interlinked applications contribute to increasing decision-making quality under consideration of uncertainty in the production environment. Context-specific data from the IoP data lake is used in the sense of a control loop to generate data-driven transparency via the various applications with regard to emerging adjustment needs and to address these by deriving and implementing suitable measures (Fig. 16.1).

The four applications developed, their specific challenges, the methods used, underlying digitals shadows, and the results obtained through interdisciplinary research are described in detail in the following Sects. 16.2, 16.3, 16.4, and 16.5. Closing, a short summary and outlook is given in Sect. 16.6.

16.2 Best Practice Sharing in Global Production Networks

The sites of manufacturing companies are often globally distributed and form complex and historically grown production networks (Lanza et al. 2019). As a consequence, the sites of these production networks have developed individually and independently of one another and exhibit differences in performance within the network (Reuter et al. 2016). Systematic knowledge transfer between different production sites is not frequently practiced, although globally active companies carry out comparable production processes in different ways at several locations (Schuh et al. 2019a). However, a systematic exchange of best practices in the global production network enables production sites to learn from each other and minimize variance in performance (Friedli et al. 2014). Furthermore, the exchange of knowledge can increase the ability to react to unexpected events by learning from the experiences of others, which makes cross-site knowledge sharing a success factor (Cheng et al. 2008). At the same time, companies face a major challenge when implementing systematic best practice sharing due to the high number and complexity of different production processes in practice (Deflorin et al. 2012).

In the field of knowledge transfer within production networks, there are various approaches that focus on different aspects. Depending on the knowledge type, several approaches suggest distinct transfer mechanisms and develop solutions to increase the absorptive capacity of the recipient (e.g., Nonaka 1991; Ferdows 2006). Often also social aspects of knowledge transfer are considered, but rarely a practical solution to increase transfer acceptance is proposed. In addition, the topic of initiating a knowledge transfer has not yet been adequately addressed, nor have the possibilities of new methods for data analysis and new information technologies for efficient preparation of the knowledge transfer. In general, existing approaches focus only on single criteria to increase the efficiency of the knowledge transfer, but to our knowledge, no approach to date addresses all needs for learning across sites from transfer initiation to transfer mechanism to empowering knowledge assimilation. Thus, there is a need for a holistic approach to enable the implementation of efficient knowledge transfer in production networks (Schuh et al. 2020a). The presented approach tries to close this gap.

16.2.1 Approach for Best Practice Sharing in Global Production Networks

The approach for cross-site best practice sharing is divided into three steps starting with the identification of the requirements for comparing production processes in production networks, followed by determining the utility for cross-site learning and finally performing an efficient and user-friendly transfer of knowledge.

The first step creates the foundation for learning across sites by enabling the comparability of diverse production processes within a global production network. For this purpose, a solution space is defined to determine which types of production processes can be compared under which conditions. In addition, a target system is defined. In this way, only meaningful knowledge transfers between comparable production processes are allowed and the motivation of knowledge transfers between sender and receiver can be maintained. This requires a description of production processes in order to identify comparable processes across sites. Following Steinwasser, a production process is defined as a composition of product and resource (Steinwasser 1996). Constituent features were developed for both product and resource. For example, a product can be described in terms of its materials, size and weight, or a resource in terms of its degree of automation, machine designation or the necessary employee skills. On the basis of the features and their values, a precise description of the production processes is possible, which is transferred into a data model to enable the data-based mapping of the process description. The sources of the required data are the company-specific information systems such as ERP, MES, PLM, or CRM. Next, a cluster algorithm is used to identify where comparable production processes exist in the production network concerning metric product and resource characteristics (e.g., product weight). If a production process belongs to a cluster is determined by the distance of the characteristics between the individual objects. For clarity, the categories material and technology are plotted on the screenshot of the prototype as an example. The points in the graph each represent a production process. The individual production processes can be entered on the graph with regard to their material and technology. It should be noted that non-numeric features (e.g., material) are converted into binary features. Production processes of a cluster are characterized by the fact that they are close to each other in the considered categories, i.e., the distance between the points in the graph is low. Currently, only two categories can be displayed next to each other in the prototype in order to analyze the differences between the clusters. An extension is being worked on to be able to determine the decisive categories in view of the large number of categories. The two other diagrams in the screenshot allow the user to further analyze the similarities. For example, they show how the various clusters (each color represents a cluster) differ in the categories under consideration. The lower diagram in particular illustrates that there is a clear division of the clusters in terms of technology. However, even here there are overlaps between two clusters that can be caused by a different category.

The decision whether the identified production processes are comparable is made by the user within the qualitative evaluation of the results and a plausibility check. The described approach is already implemented in a prototype including a feedback loop to enable the evaluation of comparability by the user. Furthermore, the prototype has already been evaluated with real data from a coupling manufacturer and it was shown that the approach allows the identification of comparable production processes, but that a weighting of the characteristics has to be done by the user to ensure plausible results (Fig. 16.2).

Fig. 16.2 App prototype for best practice sharing in global production networks

The second step of the approach is to identify the knowledge transfer needs based on the determined cluster of comparable production processes. A cluster of comparable production processes does not necessarily require a need for knowledge transfer, as these processes may already be coordinated with each other. A knowledge transfer always involves effort and should only be carried out when there is a need. Therefore, feedback from production can be used to analyze the performance of production processes. Statistical process control (SPC) is a commonly used method for monitoring processes and to automatically detect process deviations. For the implementation of SPC statistical control charts are used to systematically analyze the output of processes. Upper and lower control limits (UCL, LCL) are determined as a function of the mean value of the outputs within a process cluster (Chatti et al. 2019). For process monitoring in production networks, an adaptive control chart is required because the design parameters vary over time. For example, the width of the control limits must be adapted according to the sensitivity of the processes in a company-specific manner. As an outcome of SPC, process deviations within a cluster of comparable processes can be identified and the upper and lower control limits can be utilized as knowledge transfer trigger points.

If there is a need for learning across sites, the third step should be to make the knowledge transfer as efficient and user-friendly as possible so as not to consume too many resources and not to reduce the motivation of the sender and receiver of the transfer. Therefore, an appropriate knowledge transfer mechanism is required. Here, the right transfer mechanism depends on the type of knowledge and the background of the participants of the transfer (e.g., Chang and Lin 2015; Shen et al. 2015; Asrar-ul-Haq and Anwar 2016). Within the research work an approach to select a communication medium depending on the situation was developed. The approach characterizes a knowledge transfer situation on the basis of three groups: knowledge type (explicit or tacit/implicit knowledge, its complexity, its specificity, and its significance for the receiving unit's performance in cost, quality, and adherence to schedules), communication situation (number of hierarchical levels involved, number of knowledge recipients, degree of familiarity between the participants, prior knowledge levels of the recipients and the participants' language skills), and the urgency of the transfer (Schuh et al. 2020b). Once a knowledge transfer situation has been characterized, the relevant characteristics can be weighted using a metric and a requirement level can be calculated. Depending on the requirement level, the appropriate communication medium can subsequently be selected. For global production networks, the following media are suggested as possible means of communication: face-to-face, video/telephone conference, video/telephone call, short message, email, and the companies' intranet database. The selection of the right medium depends on the need to be able to receive feedback and whether sending non-verbal signals is beneficial. In addition, the usage effort in the context of daily application is important and influences the selection of the medium for a knowledge transfer situation.

16.2.2 Outlook of Best Practice Sharing in Global Production Networks

While the current development of the Best Practice Sharing application focuses on inducing knowledge transfer to optimize the productivity of production processes, overall productivity is not the only criterion in production system design that can be addressed using the outlined approach. Following the agenda of the International Ergonomics Association, work system design should always jointly consider the two objectives of system performance (i.e., system productivity) and human well-being (IEA Council 2020). Not only are both goals of significant value in their own right, but they also tend to complement each other, leading to an alignment of business and social goals (Neumann and Dul 2010). Expanding the framework of the Best Practice Sharing application to include an anthropocentric perspective aimed at improving human working conditions thus offers the opportunity of a more holistic approach to process optimization. First, the aspects that are considered for identifying similar processes can be extended by adding task characteristics of the involved production workers. Second, the evaluation system that is used to compare similar processes and to identify knowledge transfer opportunities can be expanded to include metrics and assessment methods that quantify the impact of the production system design on workers. Here, a special focus can be placed on the imposed physical and cognitive workload. While the outlined advancement of the Best Practice Sharing application is the subject of current research efforts, the first results are presented and discussed in the publication ▶ Chap. 22, "Human-Centered Work Design for the Internet of Production"

16.3 Supply Chain Cockpit – Improving Data-Driven Decisions in the Context of Procurement

Companies are part of complex supply chains and operate in an increasingly volatile environment (Kamalahmadi and Parast 2016). This affects procurement which focuses on the supply of external materials and parts required for the internal processes (Pereira et al. 2014). Current developments show that the complexity of companies' procurement processes is increasing, which contributes to a higher vulnerability to supply chain disruptions (Piya et al. 2020). A means to prepare for disruption is strengthening the company's resilience. Supply chain resilience involves reducing the likelihood of facing sudden disruptions, resisting the spread of disruptions by maintaining control over structures and functions, and recovering and responding through reactive plans to overcome the disruption and restore the supply chain to a robust operating state (Kamalahmadi and Parast 2016). Resilience is significantly influenced by long-term decisions which makes the design of the procurement strategy particularly important (Pereira et al. 2020). To take into account various factors that influence the procurement strategy and ensure objective decisions, data-based approaches for decision support are required. Especially for long-term decisions, the quality of data plays a major role: insufficient data quality hinders the exploitation of data-based decision support. Therefore, this approach aims at analyzing how the data-based design of the procurement strategy can increase resilience and also investigates how improving data quality can enable such data-based decisions.

16.3.1 Data-Based Design of the Procurement Strategy

Through the design of the procurement strategy, a company specifies the fundamental design of the supply processes. It determines for example from how many suppliers what type of objects are purchased (Lasch 2019). Since each manufactured product requires different articles and raw materials, and the various articles have different characteristics, the procurement strategies must be adapted accordingly (Schiele 2019). The main objective of this research is to identify "how the procurement strategy can be evaluated and designed based on internal and external data to ensure high logistics performance in an uncertain environment" (Linnartz et al. 2021). By taking into account different data sources and considering the criticality of purchased articles the complexity can be handled. This allows a systematic design of the procurement strategy that focuses on the articles with a major impact on resilience.

Existing approaches for procurement strategy design rarely use business data to assess the procurement strategy or supply risks but instead focus on qualitative assessments. In order to increase resilience in procurement, recommendations for designing the procurement strategy and an evaluation of purchased items concerning the supply risks are required. Data-based approaches are currently uncommon in the context of criticality assessment of these items, as they require an overview of various risks and criticality factors. Nevertheless, it becomes apparent that a data-based approach is necessary for such an assessment to ensure objectivity (Linnartz et al. 2021).

The proposed approach is based on a combination of action research and the CRISP-DM (Cross Industry Standard Process for Data Mining) framework for data mining projects. It builds on three action research cycles, which are detailed according to the different phases of CRISP-DM. Within the first cycle, an application is developed that supports the characterization of purchased articles with regard to supply risks. In the second cycle a calculation logic to identify success-critical purchased articles is designed, while the third cycle focuses on adapting the application to ensure general applicability (Linnartz et al. 2021).

The current results focus on the first action research cycle and contribute to increased transparency of the procurement situation. For a structured evaluation of purchased articles and supply risks, a systematic literature review was conducted. It aimed at identifying and structuring relevant supply risks that need to be considered when designing the procurement strategy. The identified supply risks were divided into five categories, including factors such as transport complexity or natural hazards. Additionally, factors to characterize purchased articles were systematically identified building on existing raw material criticality assessments. The framework for purchased article characteristics contains both supplier-related factors, like their location or delivery reliability, and non-supplier-related factors, for instance, economic aspects (price volatility, purchasing volume, etc.) or product characteristics (specialization, substitutability, etc.). It serves as the basis for implementing an app prototype that supports companies in analyzing their purchased articles.

The app prototype integrates data from the company's business information systems and classifies purchased articles based on different characteristics. The characteristics are described through indicators. In the upper part, each column represents one indicator and its expression using a vertical scale. As an example, the app contains the indicator "number of potential supplier" which is derived from past orders, material master data, and supplier master data from an ERP system. Another example is the indicator "transport distance" which is calculated using the location of a supplier. Each horizontal line represents one purchased article and its values regarding the indicators. It thus gives an overview over the specific combination of a purchased article's characteristics. Different colors enable to highlight one characteristic and further contribute to an increased transparency of the procurement situation. The app prototype further allows for multidimensional filtering. Further below, product and supplier data are linked to show how final products (left), purchased articles (middle), and suppliers (right) are connected to each other. The lines in the left part of the sankey diagram demonstrate which purchased articles are part of which final products. The lines in the right part demonstrate which supplier delivers which purchased article (Fig. 16.3).

The developed frameworks for structuring supply risks and characterizing purchased articles are the foundation for analyzing the interdependencies between article characteristics and supply risks. Further research focuses on developing a calculation logic to identify critical articles which will be integrated into the app prototype.

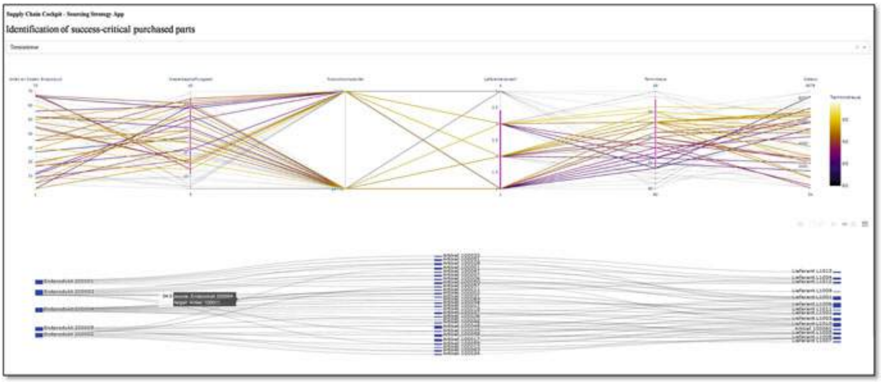

Fig. 16.3 App prototype for increasing transparency of current procurement situation

16.3.2 Master Data Quality Improvement

In the context of the *Supply Chain Cockpit*, the topic of master data quality is also being developed in an interdisciplinary research project. A crucial aspect for a data-driven procurement strategy design is the quality of the incorporated data. However, this aspect can also be applied to all other decision supports presented. Unreliable data can bear high costs for businesses and may lead to poor strategic decisions (Haug et al. 2011). Data about the most essential entities within a business, such as suppliers, employees, or materials, is called *master data*. Master data presents the fundament for many business decisions: For example, replenishment times of purchased articles are used in production planning and sourcing. While the need for high-quality master data is clear, several challenges arise regarding its realization. For one, the lack of responsibilities for maintenance of master data presents a main quality barrier (Haug and Albjørn 2011). Furthermore, a lack of both, intra- and cross-company data standards, may limit master data's fitness for shared use (Otto and Österle 2016). This occurs for example, when supplier and purchaser intend to refer to the same product, but run into issues as they each maintain their own product master data. Our work aims at developing a data ecosystem model for the procurement context which captures how master data is produced, maintained, and used. This model will serve as the fundament for an application that identifies and prioritizes data quality requirements in master data and gives actionable recommendations for quality improvements.

Data quality can be described in the form of various dimensions, such as accuracy, completeness, or timeliness. There exist approaches to identify relevant dimensions per master data class (Falge et al. 2012) and to develop master data management frameworks incorporating data quality (Otto and Österle 2016). The approaches rarely focus on illustrating the environment and contexts in which data is produced, exchanged, and used. An emerging concept for modeling such an environment is data ecosystems (Geisler et al. 2021; Oliveira and Lóscio 2018). Data ecosystem models incorporate components such as the resources of interest, the involved actors, and their relationships to each other, but also the key elements regarding the functionality of the ecosystem, such as data operators, security, and services. While there exist several reference models for general business collaborations (Otto et al. 2019), there is a need to adapt these models to the context of supply chain management and procurement.

We propose a design science research approach (Hevner et al. 2004) for developing an adapted data ecosystem model. A literature review on the "flows" of master data will be conducted, i.e., the processes in which master data is generated and maintained as well as an analysis on which master data is used in which procurement decision. Incorporating this knowledge, a first model, adapted from existing reference models, will be built. The model will be applied and evaluated on use cases and consistently refined.

As a first result, existing data ecosystem models have been analyzed and a framework for an adapted model has been developed. The framework comprises five levels. The first level specifies the business processes and involved actors. In the second level, the relevant master data is elaborated and connected to the processes from the first level. This mapping of data onto processes is used in the third level to derive data quality metrics appropriate to the context in which the data is used. On the base of those metrics, the quality of data is evaluated. In the fourth level, required functionalities are formulated, e.g., regarding security. Finally, governance aspects such as policies are contained in the fifth level. By structuring the framework into these levels, a detailed analysis of the aspects that have to be taken into account when improving the data quality is enabled.

The developed model is intended to reveal requirements for master data quality management in the procurement context as well as to highlight how data quality aspects can reduce risks and leverage opportunities in the functionality of such an environment.

16.4 Data-Driven Site Selection

Supply bottlenecks, increasing regulations and growing market uncertainties pose major challenges for global production networks and force companies to constantly adapt to new conditions (Lanza et al. 2019). In this context, the search, evaluation, and selection of potential new locations is an important factor in ensuring the future competitiveness of manufacturing companies.

According to the approaches in the literature, location factor systems are usually classified according to global, regional, and local aspects (Burggräf and Schuh 2021), but there is no consensus-based location factor system, since location factors cannot be clearly delimited and overlapping aspects exist (Haas 2015). In general, location factors can be divided into quantitative and qualitative aspects (Hansmann 1974), whereby internal and external factors (Hummel 1997) and network aspects also play a role (Kinkel 2009). Furthermore, country- and sector-specific differentiations are possible (Hummel 1997). A distinction between hard and soft location factors is also required. Hard location factors are characterized by quantitative data (e.g., wage costs, taxes) and soft factors by qualitative data (e.g., political stability, culture) (Kinkel 2009), whereby all factors must ultimately be aligned in the location evaluation. The evaluation of location alternatives is carried out using established methods such as utility value analysis (Zangemeister 1976), checklists, or country rankings (Kinkel 2009). Since these established methods require the evaluation of both qualitative and quantitative data, a large number of subjective decisions are made, especially with regard to qualitative data (Blohm and Lüder 1995). However, these evaluation methods do not fully reflect the complexity of the current environment and thus do not adequately meet today's requirements (Burggräf and Schuh 2021). Since the development of new locations is associated with high, often irreversible costs, an approach is required that takes into account quantitative, objectively assessable information in particular (Verhaelen et al. 2021). Therefore, this subchapter presents an approach for systematic and data-driven decision support in the site selection. This makes it possible to map all factors by means of exclusively quantitative data. This can increase the quality of decisions as well as the transparency in the decision-making process in order to improve site selection on a global and regional levels.

16.4.1 Data-Driven Site Selection Framework

In the following, a four-step approach is presented, which objectifies the site selection process individually for each company (Schuh et al. 2022).

16.4.1.1 Step 1: Analysis of the Industry Sector, Its Dynamics, and Competitors

The first step is to analyze the business environment in order to identify possible trends and changes. Detailed sector analyses already provide a high added value, as they deepen the understanding of the strategies of competitors, the needs of the markets, and possible future developments. Existing clusters of competitors provide valuable information about potential regions for new locations, as they, in combination with region-specific economic and political indicators, allow conclusions to be drawn about the background of past location decisions. The identified agglomeration effects have a significant influence on location decisions not only against the background of possible knowledge transfers, but also with regard to available resources (Krenz 2019). The evaluation of geocoded information on foreign direct investment in production locations is suitable for determining existing clusters. Such representations also allow for the calculation of distances and travel times as well as the combination of such data with other data sets on topography, geography, and infrastructure. Panel (a) of the GIS-supported competitor and supplier analysis shows the investment projects in production sites of foreign automobile manufacturers in North America in the period 2010 to 2019 and the identification of clusters using an appropriate density-based spatial cluster algorithm in panel (b). Furthermore, in panel (c) comparable investment projects of the automotive supplier industry are localized in the same period. The agglomeration of supplier locations within a radius of 3 h travel time around the OEM locations is clearly visible for the exemplary extract (Fig. 16.4).

16.4.1.2 Step 2: Analysis of Regional and Supra-regional Location Determinants

To further narrow down the location alternatives, potential regions are evaluated in the second step top-down with regard to relevant criteria (Wiendahl et al. 2014). The analysis is also possible without a prior industry sector and competitor analysis, but it offers the possibility of implicitly comparing one's own location assessments with those of the competition. Relevant variables should include as many dimensions as

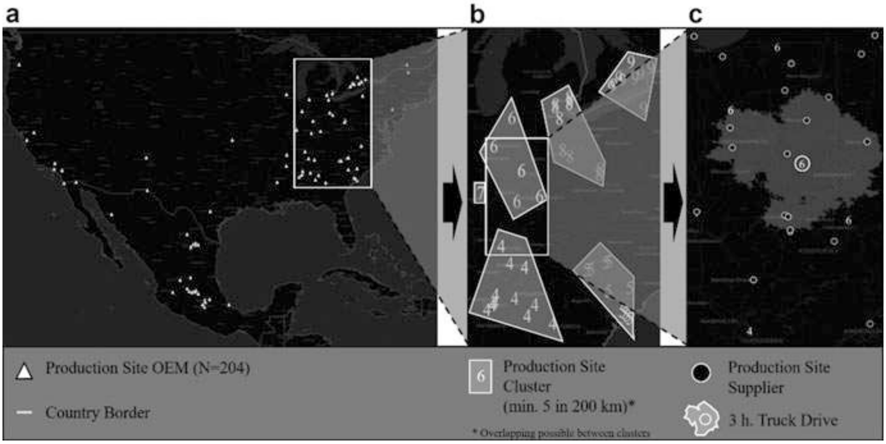

Fig. 16.4 GIS-supported competitor and supplier analysis

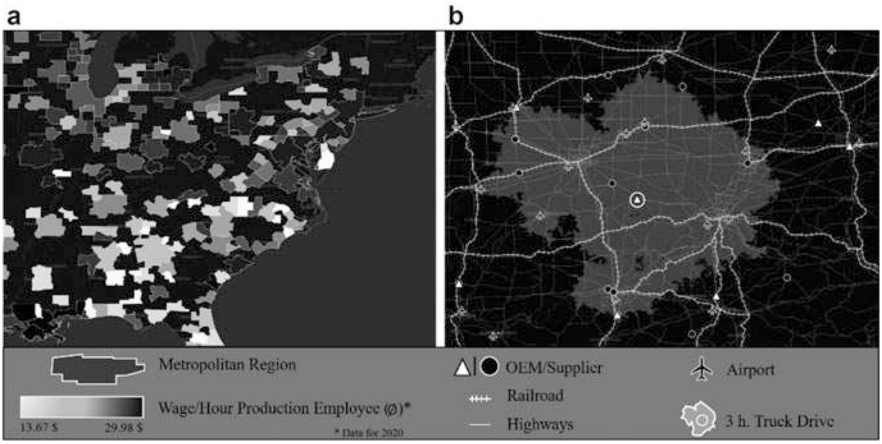

Fig. 16.5 Sample visualization of regional labor market and infrastructure parameters based on data from the U.S. Bureau of Labor Statistics and FDI Markets

possible, whereby the exact information required is ultimately case-specific and can include economic, political-economic, foreign-economic, infra-structural as well as geographical and topographical variables. In the sample visualization of regional labor market and infrastructure parameters based on data from the U.S. Bureau of Labor Statistics and FDI Markets, it is shown how the analysis is initially narrowed down from a global level to a national level (panel (a) for the eastern United States) and further to a local level (panel (b) for the Indianapolis/Cincinnati metropolitan area). It shows that significant differences (e.g., in wage levels or the availability of skilled labor) can also differ both nationally and regionally (Fig. 16.5).

16.4.1.3 Step 3: Comparison of Potential Locations Using a Target Function Method

The third step is to quantitatively evaluate and compare the potential locations. In order to integrate the large number of variables, which can be grouped into different dimensions in terms of content, into a common framework, an analysis using a target function method is suitable. The variables are standardized and combined into appropriate groups of assessment dimensions. These evaluation dimensions are then weighted. The weighing has to be defined individually for each company and even for each project. A pairwise comparison is recommended, in which the different dimensions are prioritized against each other and the weights of the assessment dimensions can be derived from this. In the methodology described, the weighting of the evaluation dimensions is the only decision to be made subjectively by the management. All other steps in the site selection process are based on quantitative data. The methodology now allows the calculation of marginal rates of substitution, a common concept in economic utility theory. This makes it possible to quantitatively assess cross-border decisions on a national, regional, and international level.

16.4.1.4 Step 4: Sensitivity and Scenario Analysis for the Ranking of Alternatives

In the last step, the ranking of the alternatives must be checked with regard to their resilience. Compared to other approaches, this minimizes the risk that the derived recommendations for action are influenced by measurement errors in the raw data or misspecification of the target function due to subjective misjudgments. Possibilities for sensitivity analyses are, for example, the (slight) variation of the weights or the variation of the indicators used. In addition to the sensitivity analysis, a scenario analysis is carried out based on the target function method. On the one hand, scenarios can concern company-specific factors, such as different forecasts regarding future growth strategies. On the other hand, scenarios can also be differentiated with regard to location factors, especially if not only present and past values are taken into account for certain valuation dimensions, but also projections about their future development. Based on the ranking with regard to the objective function and the resilience of the alternatives, the suitable location alternative can now be derived.

16.4.2 Conclusion and Outlook of Data-Driven Site Selection

This subchapter presents a systematization of site selection by means of a data-driven approach that creates the preconditions for more objective decisions compared to existing approaches. The step-by-step approach and the economic data on which the selection process is based combined with geo-information, allow better location decisions. This approach offers the user an improved understanding of the information through the data-driven approach and the underlying empiricism paired with the geo-designed visualization and provides decision support. Compared to other established approaches, the described methodology provides an increased degree of transparency and objectives in the decision process. All decision-making steps are mapped as quantitative data with regard to both soft and hard factors and are therefore transparent, measurable, and comparable. In the next steps, the approach will be expanded to include further functions. For example, an assessment of the dynamics of industries and the development of industrial clusters will be used to derive patterns. The resulting insights about future emerging regions should help companies to realize first-mover advantages by being able to develop regions at an early stage.

16.5 Sustainable Footprint Design App

The location of an industrial activity is a major influence to determine whether it is sustainable or not (Sihag et al. 2019). Depending on the environmental and societal conditions around a factory, renewable resources can be provided in different quantities (May et al. 2020). Therefore, the relocation of production processes can enhance the sustainability of a company without any changes to the processes or products. For example, water-intense production processes should be moved from regions with water scarcity to regions with sufficient precipitation to enhance the ecological footprint. To benefit from this potential, companies need to evaluate their production footprint not only with respect to their economic advantage, but should also consider the social and ecological consequences of their global production network. However, it is widely acknowledged that global production networks of manufacturing companies are one of the most complex and dynamic man-made systems (Váncza 2016). Hence, the required level of transparency is only possible with database solutions. The Sustainable Footprint Design App is a web-based application with the ability to provide decision-makers in industrial cooperation with all crucial information to evaluate the site-dependent sustainability criteria of their production network.

Several authors have identified both, the need for and the challenge of a transparent evaluation of global production networks. This section provides a brief overview of existing approaches and compares them with the unique vantages of the Sustainable Footprint Design App. Mourtzis et al. present a toolbox for the design, planning, and operation of manufacturing networks. This software required data about the plant capabilities, locations as well as the bill of materials and processes to evaluate a production network with respect to cost, lead time, quality, CO_2 emissions, and energy consumption. Other relevant sustainability criteria like water, waste, or biodiversity are not part of the evaluation scope (Mourtzis et al. 2015). The approach of Govindan et al. supports the design of a sustainable supply chain network with the use of hybrid swarm intelligence metaheuristics. Although this considers a broad variety of sustainability-related criteria, the optimization model is too complex for adaption in the industrial practice, due to its extended data requirements (Govindan et al. 2019). The web-based platform for eco-sustainable supply chain management from Papetti et al. trace supplier and their processes. Additionally, this information can be used to perform a life cycle assessment of these processes within the tool. With these features, the tool provides both transparency and a comprehensive ecological evaluation. However, the focus is on suppliers and not on intra-organizational processes (Papetti et al. 2019). The MS Excel-based toolbox of Blume is designed to evaluate the resource efficiency in manufacturing value chains. This approach includes economic and ecological criteria, but does not focus on the characteristics of production networks. It can be seen that no approach takes ecological factors into account to a sufficient extent in the design of global production networks. The following section presents an approach to this problem.

16.5.1 Approach for Sustainable Footprint Design

The Sustainable Footprint Design App allows the calculation of all ecological key performance indicators (KPIs), which can be influenced with the design of the production network. This is the case, if a site-dependent factor is combined with the characteristics of a production process. For example, a machine might need a lot of thermal energy for a production process and the possible production locations can provide either geothermal heat or fossil fuel-based heat. In that case, the difference of CO_2-Emissions can be influenced by the network design and is included in the set of ecological KPIs.

The Screenshot of the Sustainable Footprint Design App with Emission-KPIs shows how the CO_2-Emission are visualized in the app, which is based on the existing software *OptiWo* (Schuh et al. 2019b). The upper part contains a map with the locations and transport connections of the production network. The size of the arrows and bubbles presents the absolute amount of emissions, while the color represents their intensity (e.g., emissions per part). Other KPIs, which are included in the tool, are the amount of energy required by each machine, facility, and transport vehicle. For every energy consumed the corresponding emissions are calculated. In addition, the required water and effluents at each location are combined with the local water stress to evaluate the water footprint. Further, the amount recycled feedstock and waste material are estimated with respect to the local recycling infrastructure. On top of this, the land use of each location is set into context with the local biodiversity (Fig. 16.6).

Besides the described ecological KPIs there is also the option to evaluate additional ecological, social, and governmental KPIs on a holistic country level for a further benchmark of the existing production network. For an assessment of countries' ecological performance we selected 41 KPIs focusing on emission, pollution, energy, agriculture, biodiversity, resource productivity, waste, and water. Eight social KPIs cover equality and diversity, workforce, and hygiene performance of the respective country. For an evaluation of the governmental risks and opportunities of the country, six KPIs were included in the tool. In total 55 KPIs were included from

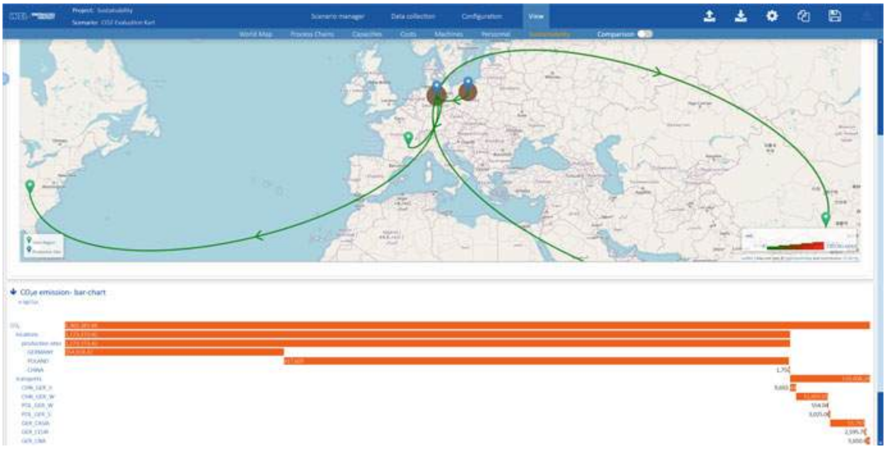

Fig. 16.6 Screenshot of the Sustainable Footprint Design App with Emission-KPIs

160 countries and with a timespan of more than 15 years ensuring an historical assessment and performance tracking. The set of KPIs is based on the following sources: United Nations Statistics Division, 2020 Environmental Performance Index Report (EPI) and the World Bank and Global competitiveness reports from 2006 to 2019. Data, which is company specific and cannot be found in public database needs to be imported by the planner from local IT-systems, such as ERP, MES, PLM, or FMS. For an assessment, the percentile rank scoring methodology is applied to calculate an overall score for each KPI per country. The calculation is based on the following aspects: countries with worse score, countries with same values, and countries with a value at all. Besides the overall score from zero to one per KPI, a best-in-category value and the respective country name are displayed. An aggregated environmental, social, and governmental score per country is also available.

The tool creates transparency for companies due to an aggregated and bundled overview of important sustainable KPIs. With this they can quickly select relevant KPIs, e.g., hiring and firing practices or the estimate for control of corruption and assess countries, which they are operating their production in, with best-in-class countries.

16.5.2 Conclusion and Outlook of Sustainable Footprint Design App

The app demonstrates how the production footprint design can enhance the sustainability of a manufacturing company. To benefit from all possibilities, a close integration with existing IT-systems like the ERP or MES is required. The design and implementation of such APIs remain a future research topic. Another challenge is the need to transfer the insights gained from the transparency of the app into strategic guidelines and operational measures to change the production network. Further, the relocation of production processes to enhance sustainability should always be a midterm solution for process technologies, which cannot be adapted easily. For a truly sustainable manufacturing company, all processes must be redesigned to reduce their negative impact on nature and society.

16.6 Conclusion

In this paper, the work of the IoP's long-term production management research group was presented. This includes four individual and partially interlinked applications that address a variety of issues in long-term production management. They pursue the common goal of data-driven decision support in the Production Control Center in order to increase the decision quality concerning uncertainty in the dynamic and changing environment. The applications presented currently differ partially in their implementation status and are continuously being developed further. This includes in particular the continued interlinking of the work within the research group as well as in the entire IoP. In the medium term, all developed prototypes are to be integrated into the IoP Kubernetes cluster, and in the long term, the real-time capability is to be increased for use in real production environments.

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Improving Shop Floor-Near Production Management Through Data-Driven Insights

17

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Abstract

In short-term production management of the Internet of Production (IoP) the vision of a Production Control Center is pursued, in which interlinked decision-support applications contribute to increasing decision-making quality and speed. The applications developed focus in particular on use cases near the shop floor with an emphasis on the key topics of production planning and control, production system configuration, and quality control loops.

Within the *Predictive Quality* application, predictive models are used to derive insights from production data and subsequently improve the process- and product-related quality as well as enable automated *Root Cause Analysis*. The *Parameter Prediction* application uses invertible neural networks to predict process parameters that can be used to produce components with desired quality properties. The application *Production Scheduling* investigates the feasibility of applying reinforcement learning to common scheduling tasks in production and compares the performance of trained reinforcement learning agents to traditional methods. In the two applications *Deviation Detection* and *Process Analyzer*, the potentials of process mining in the context of production management are investigated. While the *Deviation Detection* application is designed to

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identify and mitigate performance and compliance deviations in production systems, the *Process Analyzer* concept enables the semi-automated detection of weaknesses in business and production processes utilizing event logs.

With regard to the overall vision of the IoP, the developed applications contribute significantly to the intended interdisciplinary of production and information technology. For example, application-specific digital shadows are drafted based on the ongoing research work, and the applications are prototypically embedded in the IoP.

17.1 Introduction

Production management today faces numerous challenges such as increasing uncertainty and simultaneously growing complexity (Westkämper and Löffler 2016). Shorter product life cycles, individualization, and disruptive technological innovations require efficient implementation of changes (Schuh et al. 2017). The potential of the IoP for production management lies in providing data-driven decision support on all levels of managing production in volatile and uncertain business environments (Schuh et al. 2019a). *Short-term production management* focuses in particular on decision support in time-sensitive scenarios on or near the shop floor. Therefore, the aim of the research work is to learn and profit from historical data by developing self-learning production systems and, as a result, to significantly increase the decision-making quality and the decision-making speed in production environments (Müller et al. 2022). This is important to ensure the robustness of production processes by quickly making decisions and implementing appropriate measures (Stricker et al. 2015).

For this purpose, data and analysis latencies are to be minimized through the integration of continuous cross-domain data access and the development and combination of diagnostic, predictive, and prescriptive analytics models. Moreover, decision and implementation latencies are to be reduced by means of an appropriate collaboration of autonomous processes and model-based decision support as well as the implementation of suitable measures in the production system.

The practical realization of such decision support takes place through the development of a Production Control Center as shown in Fig. 17.1, in which interlinked applications contribute to increasing decision-making quality and speed in the production environment. Context-specific data from the IoP data lake is used in the sense of a control loop to generate data-driven transparency via the various applications with regard to emerging adjustment needs and to address these by deriving and implementing suitable measures.

The five applications developed (cf. Fig. 17.1) focus in particular on use cases near the shop floor with an emphasis on the key topics of production planning and control, production system configuration, and quality control loops. The specific challenges, the methods used, and the results obtained through interdisciplinary research are described in detail in the following Sects. 17.2, 17.3, 17.4, 17.5,

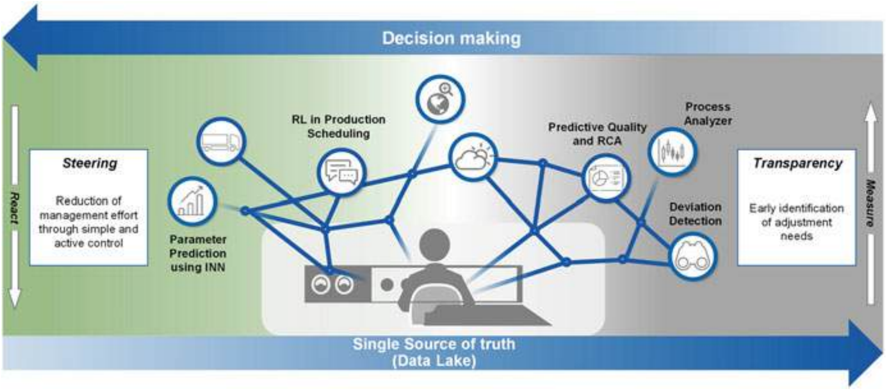

Fig. 17.1 Production Control Center

and 17.6. A summary and outlook are given in Sect. 17.7. The five applications described in this paper certainly do not address all possible challenges and problems in short-term production management, which is why further icons for future linked applications are already included in the proposed production control center (see Fig. 17.1).

17.2 Intelligent Production Management Through Predictive Quality

In order to continuously improve process- and product-related quality, data-based methods for decision support in production are being investigated as part of the Intelligent Production Management through *Predictive Quality* (*PQ*) application. The focus is on data analysis for *PQ*, which enable an early prediction of quality deviations and production defects, as well as the identification of the underlying causes. This information can then be used for deriving target-oriented corrective measures. As shown in Fig. 17.2, primarily production processes with two or more production steps are considered. This enables the investigation and development of approaches that lead to process step overarching predictions, as well as the identification of interactions between different process steps (Schäfer et al. 2019).

17.2.1 State of the Art

Currently, existing quality management methods are progressively supplemented with data-based approaches to face the challenges arising with increasingly complex products. One of the main challenges in implementing data-based decision support through *PQ* is the pre-processing and integration of diverse data sources (Groggert

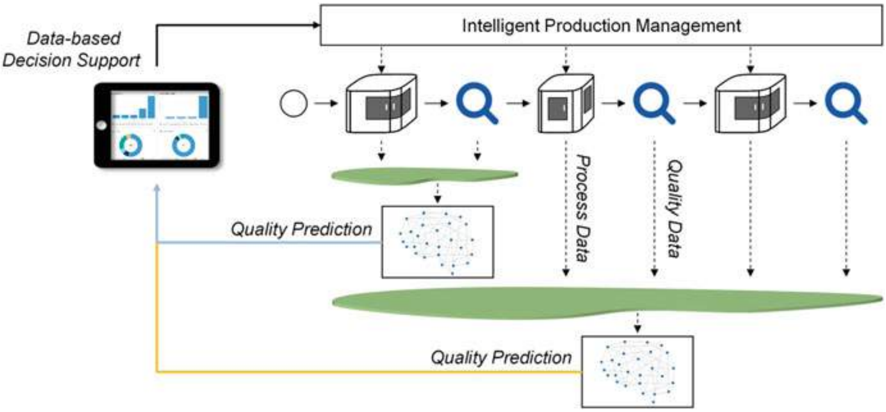

Fig. 17.2 Intelligent Production Management through Predictive Quality

et al. 2017). Due to the various sources, there are a variety of formats and data types (Wang 2017). Common data management methods, such as Data Warehouse (Bauer and Günzel 2013) and Smart Factory Information (Yoon et al. 2019), mostly consider the technical implementation rather than a clear structure for the data which is needed for *PQ* applications. This results in the necessity of a data model with a comprehensive data structure. Various information modeling standards already exist. However, they omit standardized instructions on how to perform the modeling process (Sudarsan et al. 2005). Moreover, no product-centric models for manufacturing data could be found in the literature so far.

Utilizing data structured by a product-centric data model, *PQ* is able to derive product- and process-oriented predictions about quality using data analytics methods. To subsequently optimize quality, it is crucial to get insights into the trained model (Cramer et al. 2021). Model-agnostic methods allow to detect to what extent the model prediction depends on the different input variables as well as to compare different types of models (Vilone and Longo 2021). A systematic investigation of the methods with regard to their applicability in the context of *PQ* has not yet been conducted (Goldman et al. 2021).

17.2.2 Approach and Methods

The predictive capabilities of the *PQ* application will empower the operator to improve product and process quality. For automating these operations, a universal process-independent data model is required, especially in cross-process approaches (cf. Fig. 17.2) the heterogeneity of the processes and the associated data lead to problems during analyses. To solve these, a comprehensive meta-model for production data (*MMPD*) was developed by Cramer et al. (2021), which allows the derivation of production-related data models. These universal, yet application-

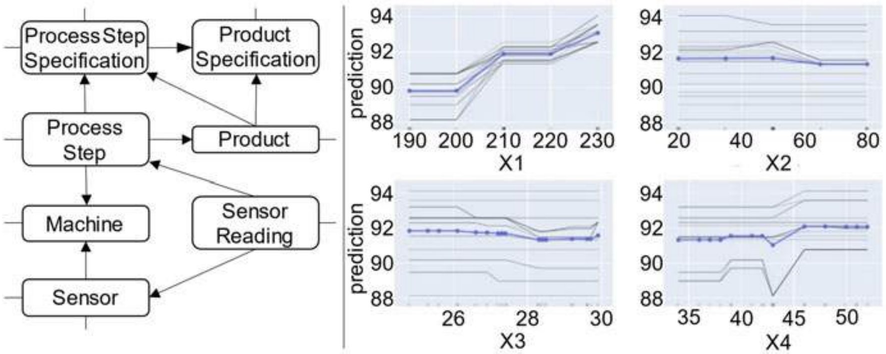

Fig. 17.3 Extract of the MMPD on the left, Partial Dependence Plot (PDP, marked in blue) with Individual Conditional Expectation (ICE, marked in gray) lines on the right

specific data models ensure compatibility between the data and the required data analysis pipelines for *PQ* applications. The *MMPD* is a product-centric model and focuses on the holistic view of product-related data. The metadata provides the ability to incorporate the domain- or application-specific context required to accurately interpret the data points (cf. Fig. 17.3). Uniform interfaces and standards for data integration and consolidation procedures allow product-centric *PQ* applications to access only the data and information they required. In this way, the *MMPD*, with the automated data analysis pipeline built on it, serves as the basis for a *PQ* application ecosystem.

To provide decision support in the optimization of production processes and quality improvement, the most important process parameters are identified and investigated. A requirement for the investigation of important features or parameters in the production process are accurate prediction models. The prediction models are used as a proxy for a simulation or a digital shadow of the production line, and it is assumed that a good prediction model captures all the intricacies of the production process that can reveal opportunities for optimization. These prediction models are trained in the data analysis pipeline discussed above, with the options of more specific or complicated model specifications if it is required.

The most influential parameters are identified with feature importance methods and on three levels of complexity. The first and most intensively researched level of investigation is singular feature importance. Singular features can indicate the most influential parameters to the prediction and by proxy, the overall quality. The second level of the feature investigation refers to the identification of interactions between features in the model. This could refer to parameters in one production step, but the more valuable outcome is finding interactions across production steps. This means the intervention or optimization point can be moved to the earliest possible step in the production line. The third level of feature importance is related to causality inference and the generation of causal graphical models that capture all relationships between parameters in the production line.

An example of the first level of investigation is partial dependence plot (*PDP*) (Friedman 2001) as the four examples in Fig. 17.3 show. The *PDP* displays the average relationship between the different values of a considered input feature and the predicted value of the target feature. For this purpose, marginalization is performed over the distribution of the feature of interest and the machine learning model prediction. As the other input features are marginalized, a function only depending on the feature of interest is obtained, including interactions with other input features. Figure 17.3 illustrates for example that higher values of input X1 lead to a higher model prediction. The *PDP* can also be used for interactions, including first and second-order effects and indicating the effect on the outcome when two features would be adjusted together. The PDP plot is enriched with Individual Conditional Expectation (*ICE*) plots, which indicate the prediction for different values of a feature of interest separately for each data point (Goldstein et al. 2015). ICE lines not parallel to the PDP indicate that there are interactions with other features. Figure 17.3 depicts that for input feature X1 the ICE lines roughly run in parallel to the PDP, which indicates that the impact of feature X1 on the model prediction surpasses the interaction with other input features. For causality representation, undirected graphical models prove to be useful by representing interactions in a digestible format, without committing to a direction of causality. Directed graphical models capture the directionality of the influences along the production line and provide a visual overview of all relationships identified.

17.2.3 Results and Conclusion

The developed *MMPD* enables the efficient use of universal data analysis pipelines for production data. Based on feature importance methods, both main and interaction effects can be detected to build causal models for root cause analysis in the future. The results presented here serve as a baseline for further work on improving product- and process-related quality. For example, this includes the integration of measurement uncertainties in model building for quality prediction. In addition, the elaboration of a concrete approach and the development of methods for the creation of causal models for production processes to determine the causes of predicted defects and quality deviations will be examined. Finally, a further necessary research priority will be focused on defining a practical way for integrating the data-based methods into established processes and workflows.

17.3 Enabling Decentralized Production by Objectifying Machine Setup Using Parameter Prediction

The events of recent years have changed the world of manufacturing. The Covid-19 pandemic demanded manufacturers of textile and plastic goods to flexibly and quickly switch their production to needed goods, such as masks or face shields (Missoni et al. 2021). Nowadays, due to globalization, companies operate in an increasingly volatile and uncertain environment and are often confronted with various types of disruptions.

One approach to address those issues is decentralized production. By switching from a centralized model with a single or few large production sites to a manufacturing environment with many smaller, widely distributed micro-factories, dependence on individual production sites is reduced and fast and flexible reactions to sudden, unforeseen events are enabled. Besides increased resilience, decentralized production networks offer many benefits, such as shorter delivery routes and times as well as a reduction in packaging material, reducing waste and increasing sustainability (Essers and Vaneker 2016; Morgan et al. 2021).

Two technologies, additive manufacturing (AM) and textile production, have proven their adaptiveness during the beginning of the Covid-19 pandemic. While traditional supply chains couldn't keep up with the demand for personal protective equipment (PPE), a Czech manufacturer of 3D printers was able to ramp up mass production of face shields in just 3 days, in which dozens of prototypes were manufactured (Prusa Research 2022). By distributing the geometry files digitally, face shields could be produced globally at short notice. A similar observation was made in the textile industry. Clothing manufacturers in Germany switched their production to masks and protective equipment in a short time, producing up to 10,000 masks per day (Oertel 2020). Moreover, material suppliers and producers were connected via a founded platform (Schmelzeisen 2020).

To exploit the potential of decentralized production, managing increasing complexity in production planning and control, and a constant part quality must be guaranteed. This is increasingly difficult in a highly decentralized system, since the type of machines, the available resources, the environmental conditions, and the operator's skill level can vary heavily. This is paired with the fact that for the presented manufacturing technologies, many process parameters are available that influence the resulting part quality and are oftentimes not fully understood. Additionally, there is a shortage of skilled workers in the above-mentioned, highly knowledge-dependent industries. In summary, to harness the full potential of a decentralized production network, the individual process must be flexible while being reliable and a defined, high-part quality must be achievable, regardless of variations in machines, material, environment, or operator skill.

17.3.1 State of the Art

The freedom and flexibility in part production via AM also entails high process complexity in form of many adjustable process parameters that influence the resulting part properties, like part strength and surface roughness, but also process factors, like manufacturing time. Those process parameters are typically adjusted for each part, based on expert knowledge or via a trial-and-error approach. Some parameters can have a significant effect on resulting part properties, like orientation on tensile strength. For example, one study found a 45.8% decrease in tensile strength between parts that were oriented horizontally and vertically on the build plate (Zaldivar et al. 2017). Currently, correlations between process parameters and part properties are mostly studied for each parameter individually. However, for a complete characterization of the process, interdependencies between parameters must be considered. For example, increasing layer height reduces the manufacturing time but increases surface roughness (Bintara et al. 2021), while reducing process speed has the inverse effect (Luzanin et al. 2013).

To handle the high amount of adjustable process parameters and their influence on part properties in various manufacturing technologies, previous studies have utilized machine learning-based techniques (Hsieh 2006; Jagadish et al. 2019; Jang et al. 2016). While typically reporting high prediction accuracies, the presented methods are not easily scalable, need a lot of computing power for each prediction, and rely on a very large set of training data.

17.3.2 Approach and Methods

To objectify the setting of process parameters in situations where high decision speed is necessary and based on a limited set of training data to achieve defined, high-part quality, an invertible neural network (INN) is set up.

The desired part quality can be achieved by several combinations of machine settings. Conventional (forward) neural networks determine the possibly achievable quality based on one particular parameter setting. INNs allow the problem to be inverted so that combinations of parameter settings are suggested to achieve the desired quality. The term INN was introduced in 2019 by Ardizzone et al. (2019). INNs differ in structure from conventional neural networks by the base layer, also called the “inverse coupling layer” (Dinh et al. 2017). In contrast with other neural networks, they can be inverted trivially. An advantage of using INNs in the AM and textile use cases is the possibility of further optimizing the production process according to certain criteria, such as production time or quality. Since different machine settings generating the same output are suggested, the most suitable ones for the specific task can be selected.

To improve the applicability of extrusion-based AM as a method for producing high-quality plastic parts decentrally, a method for non-planar AM with variable layer height was developed. Using this method, the technology’s freedom, based on a layer-by-layer manufacturing approach, is retained, while typical shortcomings like high anisotropy and high surface roughness are addressed. This is done by deliberately curving layers in three-dimensional space instead of manufacturing those layers in a planar way, parallel to the build platform. Three-dimensional layers inside the part can be shaped such that mechanical loads on the part are taken in strand direction as opposed to perpendicular to the strands. Outer layers are used to accurately represent the desired geometry, including potential freeform surfaces. This way, surface roughness can be reduced by 76% (Pelzer and Hopmann 2021), while retaining a large layer height for the majority of the part, therefore reducing manufacturing time.

17.3.3 Results and Conclusion

The benefits of agile, quickly adaptable manufacturing processes were utilized during the beginning of the Covid-19 pandemic. To aid in the need for PPE, face shields were manufactured around the world using AM. Since most people were printing the forehead part and buying elastic straps for securely wearing the face shield, the latter were in short supply. By designing a 3D printable elastic strap, setting up the associated manufacturing process while going through several iterations quickly, a highly efficient process could be set up in just 3 days. This way, it was possible to manufacture more than 800 elastic straps per day per machine. In combination with injection-molded and film-extruded parts, complete face shields could be produced in-house (Schmitz 2020). Similarly, designs for textile masks were elaborated and distributed to manufacturers who changed their production focus to masks. By setting up a supplier-manufacturer platform, it was possible to enable the exchange and distribution of close to 2 billion masks and 79 million protective clothes.

In a separate study, it was shown that using the developed INN for parameter prediction, it is possible to automatically generate sets of process parameters that are capable of accurately replicating the demanded part properties. In most cases, the accuracy of the tested part properties was within 82.76% to 99.98% of the demanded output (Pelzer et al. 2023). Only few cases resulted in lower accuracies; however, this could be attributed to extreme combinations of demanded part properties and was identified beforehand as unlikely to succeed, regardless of chosen parameters. These edge-cases were used to identify the barriers of achievable quality.

The research on non-planar AM shows that previously present conflicts, like the trade-off between manufacturing speed and surface roughness, can be resolved, resulting in a more capable manufacturing technology and higher quality parts.

In conclusion, it was shown that all necessary aspects for a decentralized production – agility and flexibility, part quality as well as reliability and objectivity in process setup – could be achieved. By combining all mentioned advances, the foundation for decentralized manufacturing is laid.

17.4 Reinforcement Learning in Production Scheduling

A general shift toward growing product individualizations and more flexible production environments has led to a significantly increased complexity in production management (Haeussler et al. 2020; Schuh et al. 2019b). Coping with smaller batch sizes, flexible material flows and frequent disturbances on the shop floor creates additional requirements especially on the short-term production management (Lang et al. 2019). Conventional ERP systems could not yet support these challenges sufficiently, so new systems continue to be developed, e.g., Advanced Planning Systems (Zijm and Regattieri 2019).

In addition to traditional optimization methods, recent approaches investigate the feasibility of applying learning-based methods, e.g., reinforcement learning (RL) to scheduling tasks in production (Xie et al. 2019). What most approaches have in common is the focus on the main control tasks order release and dispatching. By comparing the performance to traditional methods used to solve such problems, e.g., ConWIP or Shifting Bottleneck, trained RL agents show promising solutions for scheduling tasks (Kemmerling et al. 2021). Rather than a purely academic investigation of RL in abstract scheduling tasks, the goal in the work presented here is to enable the use of RL approaches in realistic production scenarios by identifying remaining obstacles and addressing them.

17.4.1 State of the Art

During the last decades of research on production planning and control many approaches and frameworks have been published (Wiendahl et al. 2005; Schuh 2012; Lödding 2016). In accordance with Lödding, general production control tasks, e.g., order release and dispatching, with short-term influence on the production performance still get special attention in order to cope with the stated challenges (Kemmerling et al. 2021; Waschneck et al. 2018). As depicted in Fig. 17.4, the order release task determines the time and sequence in which orders are released for production and thus controls the actual input to the production system. Dispatching or sequencing determines the sequence in which orders are processed at each work system (Lödding 2016).

With a growing level of complexity, especially for flexible material flows and a high number of machines and orders, classical approaches like mathematical optimization were complemented by heuristics to reduce the scope of consideration (Samsonov et al. 2021). Due to an increasing operational use of assistance systems based on simulation, it becomes feasible to depict and hence understand a higher complexity level as present methods could provide (Rabe et al. 2008). In the production context, discrete-event simulation is broadly used to map the production

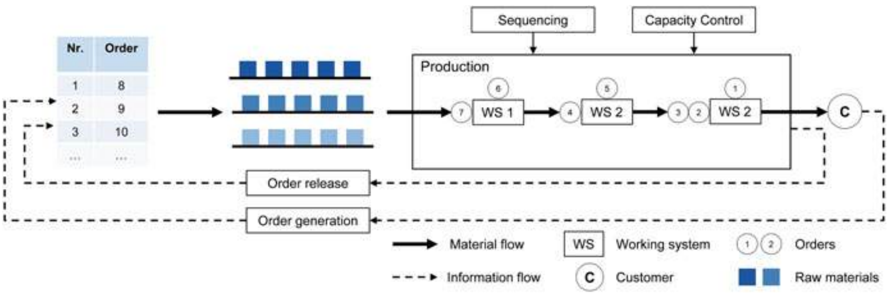

Fig. 17.4 Task of production control (Lödding 2016)

process including orders, resources, material flows, production plans, buffers, sequences, and performances (Fishman 2001). Discrete-event simulations provide the foundation for the application of learning-based methods such as RL.

The application of RL to scheduling problems in production is an emerging field of study with a wide range of different approaches being investigated. They differ in their structure as single-agents (Samsonov et al. 2021; Zhang et al. 2020) or multi-agent systems (Waschneck et al. 2018), use different kinds of algorithms such as value-based (Waschneck et al. 2018; Samsonov et al. 2021) and actor-critic methods (Zhang et al. 2020), and consider different ways of modeling state and action spaces. RL is well suited to be applied to scheduling problems, because a strategy can be derived by direct interaction with unknown environments and without having to rely on externalized expert knowledge (Panzer and Bender 2022).

While the problem has been receiving increasing attention in the literature, the focus of present works tends to be on solving heavily abstracted problems rather than researching the transfer of RL systems to real production environments.

17.4.2 Approach and Methods

Solving a problem using RL requires formulating it as a sequential decision problem, in which an agent interacts with an environment by performing certain actions after observing the environment's state. The agent receives a reward depending on how well it solves the given problem and, during a training period, learns a strategy that maximizes its long-term rewards. The agent's observations in response to actions are typically computed by a simulation (Gosavi 2015). While commercial, widely accepted simulation tools for order release and other production scheduling problems exist, they generally do not provide interfaces which allow them to be used by common RL software. RL libraries and frameworks tend to be written in programming languages like Python, which offer advantages such as easy adaptability for research, but do not provide the sufficient standard for direct implementation in an industrial application. Compatibility with commercial simulation tools is, however, of paramount importance to enable the use of RL learning in real production environments. To facilitate this, an interface based on network sockets was created for the practical application of the use case presented here (Kemmerling et al. 2021). This makes it possible for the RL agent created in Python to communicate directly with a simulation in the commercial tool Plant Simulation.

As the user acceptance of automated scheduling agents must be assured, an application to compare and visualize different order release scenarios based on their performance in terms of the adherence to delivery dates and utilization of available resources has been developed. The integration of real problem cases into the application and the combination of the different functionalities in an online application, i.e., simulation, RL algorithm, and visualization for different scenarios, ensures the precise aim of solving practical problems.

17.4.3 Results and Conclusion

Research performed during the development of the application presented here has investigated both order release (Kemmerling et al. 2021) as well as combined order release and sequencing problems (Samsonov et al. 2021) and demonstrated that RL agents can learn successful strategies to solve such problems. In addition, RL agents trained in this way have been shown to solve order release problems within the software Plant Simulation (Kemmerling et al. 2021), which is an important step toward practical use of RL in real-world scenarios. However, this transfer onto commercial simulation software also highlights the remaining challenges, which need to be overcome by RL solutions. These include incorporating further optimization objectives and constraints such as adherence to delivery dates, scaling the approach toward larger problem instances as they are encountered in real production scenarios, and transfer learning over different types of production. Further challenges lie in the investigation of how well RL solutions can perform disturbance management to appropriately respond to production interruptions and in examining how online optimization with RL can affect response times.

17.5 Process Analyzer – Weakness Detection in Event Logs

For companies, business process improvement is becoming more important (Schmelzer and Sesselmann 2020). One of the key tasks within business process improvement is the weakness detection during the process analysis phase (Dumas et al. 2018). Based on workshop formats and interviews, these approaches are time-consuming, cost-intensive (Schmelzer and Sesselmann 2020), and exposed to subjective influences (Bergener et al. 2015). For process mapping, process mining discovery algorithms can increase the objectivity and reduce the effort by analyzing event logs (van der Aalst et al. 2021). For weakness detection in process analysis, however, methodological knowledge is needed to analyze an actual process flow and ensure applicability in practice (Bergener et al. 2015). The Deviation Detection application focuses on the automatic detection of definitions as well as root cause analysis using machine learning techniques, while here the focus is on the user-defined deviation. The main objective is to bring user domain knowledge into the framework.

17.5.1 State of the Art

Various approaches from the literature aim to address the explained challenges. Authors like Bergener et al. (2015), Hoehenberger and Delfmann (2015), and Rittmeier et al. (2019) use weakness patterns that formalize knowledge about the structure of process weakness types to apply them to process models with pattern-matching algorithms. In approaches such as Outmazgin and Soffer (2016) this idea

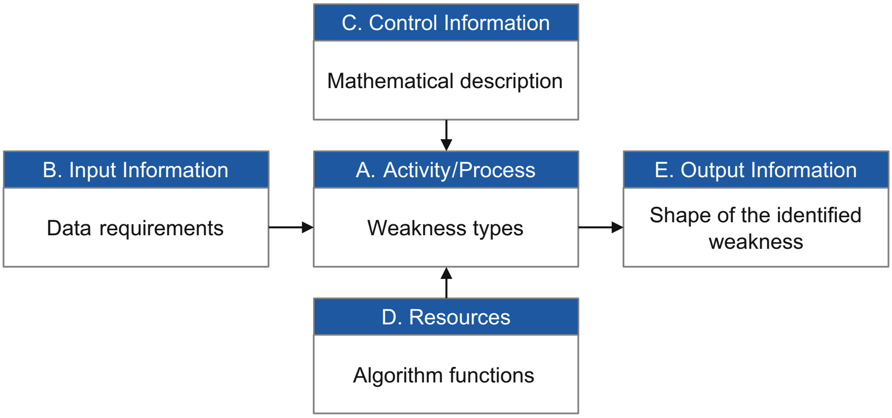

Fig. 17.5 Elements of process weakness type model (Schuh et al. 2021)

is applied to event logs, but only for specific workaround weakness types. Hence, huge automation potential remains for the weaknesses identification in real business processes with low effort. Several process mining techniques for general weakness detection do already exist but often rely on reference "to be" process models. The remaining challenge is to develop weakness models of generic business process weakness types. Their application on event logs enables weakness detection in as-is-processes without a reference model and hence can reduce effort and subjectivity.

17.5.2 Approach and Methods

The Process Analyzer enables semi-automated detection of weaknesses in business and production processes based on event logs. To this end, domain expert knowledge on relevant process weakness types is transformed into weakness models, which are applied with algorithms to event logs.

A weakness model is the formalized description of a weakness type with regard to its characteristic properties (Schuh et al. 2021). The graphic description method IDEF0 (**I**CAM **Def**inition for **F**unction Modelling) is used as a framework for the modeling of process weakness types. IDEF0 models consist of five elements: *Activity/Process, Input Information, Control Information, Resources*, and *Output Information* (Presley and Liles 1995). It can be applied to describe weakness models using the elements *weakness type* and *data requirements* necessary to detect a weakness, a *mathematical description* as a rule for detection, *algorithmic functions* that enable the application of the weakness model as well as the *shape of the identified weakness* (e.g., event, tuple of events, . . .). Figure 17.5 shows a generic model for process weakness types.

17.5.3 Results

Seven generic **weakness types** were derived from systematic literature followed by a multi-criteria relevance assessment by Schuh et al. (2021): A *redundant* activity describes the repeated execution of a single activity within a process instance. A repetition of an activity sequence within a process instance is labeled as a *backloop*. Unwanted activities that occur at least once (e.g., printing) represent the weakness type *unintentional activity*. *Parallelizable activities* indicate a reduction in lead time in comparison to sequential execution. The potential for activity acceleration is addressed by the weakness type *unsuitable execution time*. A *bottleneck* is an activity in a process instance with the longest execution time. *Transition times* specify the time between two consecutive events, which is generally considered a process weakness.

Regarding the **data requirements**, all the mentioned weakness types require the basic event log attributes, process instance, activity, and time stamp for identification. Additionally, the weakness types *unsuitable scope of activities, bottleneck,* and *transition time* require start and end timestamps for each event.

The **mathematical description** of weakness follows the consideration that algorithms must be able to process the information from event logs. To ensure practical relevance the concept's database is the event log, which is a set of events stored in the information system. In this work, the mathematical rule-based description of an event i is defined as:

$$i = (m, n, o) \text{ or } i = (m, n, o_i, o_e) \tag{17.1}$$

with i = event; $m(i)$ = process instance of event i; n(i) = activity name of i; $o(i)$ = timestamp of i; $o_i(i)$ = initial timestamp of i; $o_e(i)$ = end timestamp of activity i

The given attributes $m(i)$, $n(i)$, and $o(i)$ or $o_i(i)/o_e(i)$ are variables, specific values of these attributes are indicated with "*". Following, the mathematical descriptions are derived for the example of the weakness type *redundant activity*. The set $I(m*, n*)$ is defined as all events in the event log with a specific process instance $m*$ and specific activity name $n*$:

$$I\ \left(m^*, n^*\right) = \left\{i \in I \mid m(i) = m^* \wedge n(i) = n^*\right\} \tag{17.2}$$

The set $I(m*, n*)$ equals all redundant activities that occur more than once in a process instance, leading to a mathematical description for a *redundant activity*:

$$\mid I\ \left(m^*, n^*\right) \mid > 1 \rightarrow I\ \left(m^*, n^*\right) = \text{“redundant activity”} \tag{17.3}$$

In practice, this means that the weakness type "redundant activities" exits, if a process instance contains two events with the identical activity name. Based on the mathematical rule-based descriptions, Schuh et al. (2021) defined nine **algorithmic**

requirements on how to apply the models to event logs. In the context of this paper the requirements have been translated into a pseudo-code, which is followingly illustrated for the weakness type of redundancy:

for each activity in the set of events in the event log:
for a process instance in Process Instances (as a set of process instances in the event log)
if count of number of activities in process instance > 1:
then return duplicate activity found

Using this structure, the requirements for an executable algorithm can be derived. For the process analyzer, algorithms were designed and tested using simulated data generated from real event logs (Pourbafrani et al. 2021a). The provided platform allows to generate event logs with known deviations and assesses whether the formal definitions are able to catch these deviations.

17.5.4 Conclusion

With increased pressure on process performance, also the effectivity and efficiency requirements for the methods for business process improvements increase. By process weakness type modeling and algorithmic implementation, the process analyzer enables automated weakness detection in event logs, thus offering significant reductions in effort and subjectivity compared to conventional approaches in practice. Further research should address the quantification of performance losses due to process weaknesses as well as the standardized derivation of measures including the quantification of their impact on process performance. Combined, those concepts could serve as holistic decision support for process analysis and design, which is already being pursued by the authors.

17.6 Deviation Detection in Production Lines Using Process Mining

In order to meet the high customer requirements in terms of individualized products and short delivery times, global supply chains with strong interdependencies have formed in recent decades. In order to absorb possible external and internal disruptions, it is necessary to build robust production systems. The response to disruptions in production is the task of the production controller. The task of the production controller is to make high-quality decisions in a short time. Furthermore, the production systems and the dependencies between the subsystems are complicated, and because of this, it is difficult for one person to derive suitable countermeasures. The complex processes of production planning and control require appropriate decision support so that the decision quality can be improved. In the current case, however, there is a lack of suitable IT support, so that complex decisions are primarily made on the basis of experience. Often, the production controller is insufficiently supported by IT systems and therefore relies on experience. In the area of production planning and control, it is expected that decision support systems will improve the decision-making processes and reduce the probability of making the wrong decisions. The recorded execution data of production systems is a great source of information that can be used to support production controllers in deviation management. This information is transformed into the form of event logs in the context of process mining. The aim of this research is to create a decision support system to enhance the decision-making quality on the shop floor (Mühge 2018; Fischer et al. 2020). This chapter presents a framework and demonstrator for the management of detection and reaction of disturbances on the shop floor by using process mining and machine learning. Compared to the application Process Analyzer, this application supports daily operational decisions on the detection and handling of disturbances automatically, whereas the Process Analyzer application is based on the user's input for the definition of deviations. The following chapter presents how the framework and demonstrator have been approached within the context of the Internet of Production.

17.6.1 State of the Art

To understand disturbance and deviation handling, deviations and disturbances are defined. Unplanned and unforecasted deviations from the planned status are referred to as disturbances. These result in production shortfalls or performance reductions without intervention (Schwartz 2004). Deviations are characterized by comparing planned and actual values. Deviations do not necessarily have negative consequences for a production system, while disturbances normally have. If a defined tolerance range is exceeded, deviations are classified as disturbances due to the negative effects on the production system. If the tolerance range is regularly violated, this is referred to as systematic disturbance. One of the typical tasks of production controllers is to manage the performance of production, so reducing the negative impact of disturbances is particularly important (Meissner 2017).

The state of the current research in this fields aims to support the production controller in automatic disturbance handling. Existing approaches in the field of disturbance management by production controllers can be divided into simulation-based support, methodical support, process mining techniques, and machine learning-based support. The machine-learning-based approaches use case-based reasoning for knowledge representation for a rescheduling approach (Priore et al. 2015; Khosravani et al. 2019). Other approaches use Support Vector Machines (SVM) or complex event processing for the prediction of deviations and disturbances.

In this research, the focus is on process mining techniques since they are data-driven and use historical event data to interactively improve processes (Pourbafrani et al. 2021a). Each product in a production system is a process instance, and the recorded process instances are able to reveal performance and compliance deviations and potential root causes. Process mining deviation detection approaches are aligned and supported by machine learning techniques (Pourbafrani et al. 2021b), which makes providing a novel deviation detection framework for production lines possible.

17.6.2 Approach and Methods

To develop a first demonstrator, a framework for decision support systems (DSS) was developed based on the structure proposed in Sauter. DSS is described as an IT-based system that enables the user to access context-relevant data, analyze it, and evaluate different alternatives for a specific decision situation (Sauter 2010). Due to the tasks of the DSS, it is structured into three parts, namely, a data module, a model module, and a user interface (Sauter 2010). In the following, the adapted framework for deviation detection and its components will be described. The data component uses feedback data from production and machines and has the task of gathering data from different enterprise IT-Systems like ERP, MES, or IoT platforms to combine as much data as possible to enable the comparison between the actual and planned states of the production system. The data component will provide the data in the form of an event log, which is needed for the *process mining* and the later machine-learning components (Fig. 17.6).

The framework consists of three main modules. The first module is process mining, which discovers the current process flow of the products and orders in progress. Process mining not only enables the representation of the actual and planned process flow but also enables the identification of deviations in the actual process and in comparison to its planned flow. The set of labeled deviations in the context of performance and conformance that the framework is able to identify is presented in Fig. 17.6. The identified deviations will then be labeled in the second

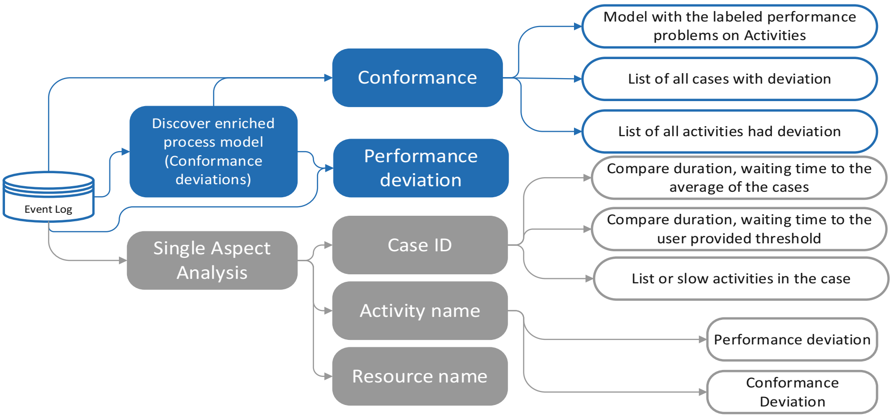

Fig. 17.6 The defined and considered list of deviations w.r.t. performance and activity flow in the production lines using their event logs

module by a machine-learning algorithm, and it will be checked if they are a disturbance. Afterward, the potential causes of the detected disturbances are identified, which can be used as a recommender system for similar disturbances in the future. This represents the third module of the framework. The process flow, identified deviations, and labeled disturbances, as well as the proposed countermeasures from the recommended system, will be presented to the production controller in the user interface. There, he can give feedback to the model component on whether the disturbances were labeled correctly and if the recommended countermeasures were suitable. With the feedback, the model components are trained continuously and enable a continuous improvement of the DSS.

17.6.3 Results and Conclusion

The framework was implemented as a Python web application. With the process mining algorithms, deviations are detected w.r.t. activities, resources, process instances (cases), and the overall processes. Afterward, using different techniques such as decision trees, the decision trees are trained using the detected deviations. The resulting trees are able to present the potential causes and situations that lead to the specific types of deviation happening. The causes are identified, and countermeasures are proposed. Furthermore, the application of process mining was evaluated in the context of a pipe manufacturer. A sample-derived decision tree can be based on the duration of process instances as a deviation in the application.

The purpose of the proposed framework is to identify and react to disturbances in production lines w.r.t. their event logs. The framework and its modules were designed and implemented to make the evaluation using real data possible. This framework was evaluated using simulated event data and real-world data of processes in the Cluster of Excellence "Internet of Production" project with the main purpose of making decisions within certain constraints. The comprehensive considered types of deviation and extracted attributes are the proper platform for the use of predictive process monitoring in the case of online detection and reaction of deviations in production lines. The next step is to make the framework executable for the streaming data of production lines, which requires deployment on the actual shop floor settings.

17.7 Conclusion

In this paper, the work of the IoP's short-term production management research group was presented. This includes five individual and partially interlinked applications that address a variety of issues in short-term production management. They pursue the common goal of data-driven decision support in the Production Control Center in order to increase both the decision quality and the decision speed in production environments on or near the shoop floor. The vision of the self-learning production system, in which learning and profiting from historical data are intended, is central to this. Subsequently, the context-specific selection and processing of data provide the basis for the research contributions achieved in the various applications.

Regarding the *Predictive Quality and automated RCA* application (17.2), three major research contributions are made: defining a comprehensive data model and an exhaustive ML framework, quantifying uncertainty for predictive models, and using feature importance as well as other model-agnostic methods to gain process insights. A similar contribution is made with the application *Parameter Prediction using INN* (17.3). By training an invertible neural network based on historical and synthetically generated data, process parameters are predicted which can be used to produce components with the desired quality properties.

The application of *RL in production scheduling* investigates the feasibility of applying reinforcement learning to common scheduling tasks in production and compares the performance of trained reinforcement learning agents to traditional methods used to solve such problems (17.4). While reinforcement learning shows promise, it has to be pointed out that challenges such as scalability and compatibility with common simulation software remain.

In both applications *Process Analyzer* (17.5) and *Deviation Detection* (17.6), the potentials of *process mining* in the context of production management are investigated. While the *Deviation Detection* application is designed to identify and mitigate performance and compliance deviations in production systems, the *Process Analyzer* concept enables the semi-automated detection of weaknesses in business and production processes utilizing *event logs*. By using *process mining* techniques on *event logs*, effort and subjectivity for the weakness detection in as-is-processes can be reduced without requiring a reference process model.

The applications presented currently differ partially in their implementation status and are continuously being developed further. This includes in particular the continued interlinking of the work within the research group as well as in the entire IoP. In the medium term, all developed prototypes are to be integrated into the IoP Kubernetes cluster, and in the long term, the real-time capability is to be increased for use in real production environments.

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Part VI

Agile Development

Agile Product Development for Cyber-Physical Products

18

Günther Schuh, Wolfgang Schulz, Maximilian Kuhn, and Christian Hinke

Contents

Abstract

The manufacturing industry, especially in high-wage countries, faces new challenges in recent times. The environment of development projects gets more dynamic and uncertain and is characterized by fast-paced changes of technological and economical aspects as well as heterogeneous customer requirements and

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volatile markets. In combination with an increasing complexity of cyber-physical products, the challenges within product development are constantly growing. Furthermore, companies need to be more flexible and be able to adjust to changing conditions (Schuh & Dölle 2021, S. 11). To increase flexibility, enablers (i.e., advanced manufacturing technologies) and tools (i.e., data-based automated design tools) are presented, whose further development and integration into the product development process reduce development times. Agile product development for cyber-physical products has become a significant research focus in order to meet the challenges described and to ensure the future competitiveness of manufacturing companies. The following paper and respective sections will describe the vision and main research activities within the Cluster of Excellence "Internet of Production" (IoP) in the context of agile product development for cyber-physical products.

18.1 Introduction and Research Objective

The Cluster Research Domain C (CRD-C) "Agile Product Development" focuses on the determination of processes, structures, as well as enablers and tools for agile product development for cyber-physical products. In this context, the Internet of Production allows stakeholder integration for an effective development and eliminates latencies for radically reducing development lead time. Multiperspective and persistent datasets within the IoP are an absolute precondition for the implementation of agile product development in manufacturing companies as an opportunity to confront today's volatile market conditions.

Conventional plan-oriented development approaches are reaching their limits in terms of dealing with the radical reduction of development times (Kantelberg 2018). Particularly in the context of cyber-physical systems, the fulfillment of functions by sub-functions of the various domains of mechanics, electronics, and software leads to major challenges in development (Drossel et al. 2018). Thereby, the linking of physical and data processing virtual objects results in a significantly more complex product and its development process. Over the past years, research focused on the acceleration of the pace of adaption and the improvement of agility within product development (Cooper & Sommer 2016). Whereas agile procedure models are popular within the software industry, a systematic transmission of the advantages of these models on the development of cyber-physical products is still pending.

This is due in particular to changed restrictions in the software industry compared to cyber-physical products within the manufacturing industry (Cooper & Sommer 2016). In addition to existing organizational hierarchies and the willingness of employees to change, the significantly increased effort required to implement prototypes should be mentioned in particular in this context (Schuh et al. 2017a). Furthermore, there is a need for synchronization and coordination of the development streams with regard to required information from and for the various disciplines in order to enable rapid and flawless development. Therefore, the CRD-C "Agile Product Development" addresses the following main objective:

To enable agile product development for cyber-physical products in terms of radical reduction of lead time while at the same time enhancing customer satisfaction.

The reduction of lead time and enhancing of customer satisfaction can be achieved by changing the conventional and plan-driven development approach toward an agile process. Therefore, the IoP supports the databased determination of product concepts as well as the related constraints and offers a possibility to deal with unpredictable environmental changes. Accepting and handling uncertainties during the product development process means overcoming the typical completeness paranoia, which describes today's demand of full specifications prior to a development activity. Databased tools as well as advanced manufacturing technologies allow a new way of stakeholder integration resulting in exceeding customer and user expectations. The direct integration of stakeholder feedback in terms of rapid engineering change requests also allows the derivation of even more suitable products. In order to answer this question, the research domain is subdivided into the two focus areas and respective workstreams "Processes and Structures" and "Enablers and Tools" for agile product development, which are introduced in the following sections.

18.2 Processes and Structures for Agile Product Development

The first research area focuses on processes and structures for agile product development. In terms of processes, the market development, engineering and production of prototypes must be evaluated. Furthermore, the necessary structures in terms of organization and data structures for an agile product development in the context of the IoP are derived. Thus, the following research questions structure the research in this field:

1. How should agile processes and methods be designed to support market development, engineering and production of prototypes?
2. How should agile organizational structures be designed and how can an agile culture be implemented?
3. What are the data structures needed to eliminate semantical conflicts and latencies?

The first question addresses agile processes and methods. The IoP differentiates between the three areas market development, data and engineering, as well as production of prototypes. Accordingly, underlying procedure models are derived considering multiperspective and persistent datasets. In this context, the systematic transmission of the advantages of agile software methods on cyber-physical products is addressed. The respective organizational structures in combination with an agile culture enable the realization of advantages. Finally, the processes are enhanced as transparent exchange of data along the process erases latencies and semantical conflicts. In order to reflect the relevant literature with respect to processes and structures for agile product development, state of the art is discussed in the following.

18.2.1 State of the Art

The SCRUM approach constitutes an established agile method for the software industry. A key element is the definition of iterative cycles named sprints creating a testable, functional product increment (Schwaber 2004). Smith considers the requirements of manufacturing companies for implementing agile processes (Smith 2007). Klein additionally provides promising approaches toward agile engineering (Klein & Reinhart 2016). Cooper as well as Ahmed-Kristensen and Daalhuizen presented approaches constituting an integrated approach of the conventional Stage-Gate process and agile methods (Cooper & Sommer 2016; Ahmed-Kristensen & Daalhuizen 2015). Conforto defined an iterative development approach integrated into a Stage-Gate process (Conforto & Amaral 2016). The authors' prior work concerned the development of physical products as well as the design of innovation and development processes. The SFB 361 focused methods to increase development effectiveness and efficiency. In addition, several researchers have contributed to the research on agile product development in the context of the manufacturing industry (Schuh et al. 2017a; Rebentisch et al. 2018; Schloesser 2020; Kuhn 2021). Nevertheless, the described approaches do not emphasize the design of agile processes supporting the collaboration of different cross-domain departments in different types of development sprint. In addition, the approaches do not concretize organizational and data structures.

18.2.2 Overview of Research Areas Within "Processes and Structures"

The focus of the research area "Processes and Structures for Agile Product Development" lies on processes and respective methods as well as organizational structures and data structures for agile product development. Therefore, "Processes and Methods" address the derivation of the underlying procedure models. The research field "Organization" discusses working structures as well as the implementation of an agile culture. To build a connection toward the IoP as the main driver for the databased reduction of latencies, the research field "Data" covers the development of a digital shadow for the entire engineering-oriented value chain of the development cycle. Furthermore, this research field comprises the requirements of the tools of the development cycle regarding the IoP (see Fig. 18.1).

In order to radically shorten the development time and increase customer and user satisfaction, the IoP offers several possibilities in terms of stakeholder integration and latency reduction. Within the area of "Processes and Methods,"

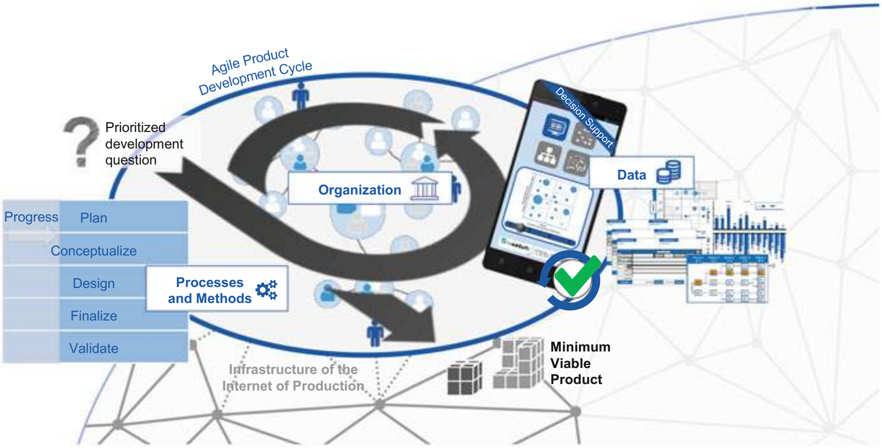

Fig. 18.1 Conceptual overview of processes and structures for agile product development

the three research fields "Market Development," "Engineering," and "Production of Prototypes" concentrate on the systematic transmission of the advantages of agile software methods to the development of cyber-physical products and therefore contribute to realize the potentials of agile product development for cyber-physical products. In order to define an underlying procedure model for agile development, the sprint targets (e.g., market teaser, feasibility, functional prototype, etc.) are taken into account. In addition, the definition of target-dependent sprint lengths as well as necessary IoP-based tools to address the identified latency drivers is required. The definition of the sprint types also shows a strong connection to the definition of working structures within the research field "Organization" as roles and team composition depend on the sprint type. Synchronization of the different sprints is important to ensure the effectiveness and efficiency of cross-domain product development. Multiple agile sprints are combined into one overarching development cycle. This development cycle can vary in length and has the primary goal of answering a set of central development questions and reducing uncertainty in the development project. Development questions are derived from the core requirements that are expected to achieve high customer satisfaction. The focus on a few significant development questions, instead of a complete specification list, represents a paradigm shift in product development and supports the rejection of the so-called completeness paranoia. The validation of the development questions is achieved with the involvement of different stakeholders and the generation of minimum viable products (MVP). MVP are (virtual or physical) "extracts" from a product. Based on a generated minimum viable product, different stakeholders can provide feedback regarding selected development questions so that the next development cycle can be pursued. The early uncertainty reduction and knowledge generation with the help of the iterative generation of minimum viable prototypes or product increments is a crucial characteristic within agile product development

(Riesener et al. 2019). In addition to the previously described processes and methods, respective structures need to be acquired. The research field “Organization” focuses on agile working structures and teams as well as the implementation of an agile culture. First, the necessary members within an agile development team have to be defined. The so-called voice of the product exists, for example, in the form of a group of project managers who hold overall responsibility. As another example, cross-functional team members participate depending on sprint target, process type, and targeted viability of the sprint outcome. In conclusion, the combination of hierarchical organization with lateral working structures can be a solution, as it supports direct communication (lateral structure) as well as instant decision-making (hierarchical organization). Moreover, culture and acceptance are important for the transformation toward agile product development. Management principles, values, and working environment present some of the main factors, whose adaption becomes necessary in the context of agile processes. In addition, the analysis of behavioral patterns provides further information about the acceptance of agile product development. Due to the networked and cross-company collaboration in today’s development projects, it is not sufficient to focus the design of the company organization, but the scaling of agile product development in development networks must also be organized. The last field of research addresses data structures, thus depicting an important part for the connection of agile product development and the IoP. To support the agile development processes, a transparent, legible, and plausible exchange of data is necessary. Such a structure allows the provision of data aggregated according to the requirements of the operator, without semantical errors. Furthermore, the data structure supports system orientation. Whereas nowadays, experts work domain oriented (e.g., mechanics), the aggregation of data without semantical errors allows the consideration of different domains by each expert (Mauerhoefer et al. 2017). In this regard, the approach of model-based systems engineering (MBSE) becomes crucial for the realization of agile product development.

In summary, the described structure of the “Processes and Structures” and the included research fields form the basis for the realization of agile product development in the context of the Internet of Production. The tools to be developed in this context take into account the implementation of development cycles based on development questions for the generation of minimum viable products. With focus on the definition of agile processes, the collaboration in different process types can be improved in all areas in the IoP. By concretizing an agile organization for the own company and also across companies in the network, cross-domain teams including the required roles and responsibilities are defined as a required part of agile product development. Semantic conflicts and latencies can be eliminated by identifying the required data structures. The IoP also improves stakeholder integration and helps to increase customer and user satisfaction and acceptance.

18.3 Enablers and Tools for Agile Product Development

The present chapter, in general, focuses on the determination of structures, processes, and methods as well as enablers and tools for agile product development for cyber-physical products. The following second part of the chapter focuses on the research of enablers (i.e., advanced manufacturing technologies) and tools (i.e., data-based automated design tools) and their sufficient integration in agile product development processes. The following research questions structure the research in this field:

1. How can advanced manufacturing technologies and data acquired from corresponding prototypes be used and integrated to enable agile product development?
2. How can relevant data from production and material be used to determine the minimum viability of a product increment as well as to select, adapt, and improve the corresponding prototyping technologies?
3. How can relevant data provided by the IoP be integrated into automated and interactive design tools to support continuous stakeholder integration as well as latency elimination and thereby enable agile product development?

The first research question focuses on advanced manufacturing technologies and their qualification for an efficient and rapid realization of market teasers, feasibility studies, and functional prototypes. Beyond the determination of the minimum viable product increment and the corresponding prototyping technologies, the second research question addresses the actual technological limitations of prototyping technologies. In this context, the data gathered during the production process of the product increments supports the continuous process optimization of advanced manufacturing technologies. Finally, the focus of the third research question – the ubiquitously available data, information, models, and knowledge across user, production, and development cycle provided by the IoP – has to be condensed into design-specific digital shadows. The respective tools considering the data from user, production, and development cycle support the developer within the different sprints in terms of easy-to-use applications. In order to reflect the relevant literature with respect to enablers and tools for agile product development, state of the art is discussed in the following.

18.3.1 State of the Art

Concerning manufacturing technologies efficiently transferring digital design data into physical products, additive manufacturing (AM) and more general advanced manufacturing technologies (AMT) are growing fields of international research

(Gu et al. 2021; Poprawe et al. 2018; Behera et al. 2013). In particular, metal AM is of increasing interest, and several international research groups are working on this topic (Baumers et al. 2016; Zaeh & Ott 2011).

Research at the RWTH Aachen University via the Cluster of Excellence (CoE) “Integrative Production Technologies” in the field of AMT focused on direct, mold-less production technologies – especially metal AM (Poprawe & Bültmann 2017), hybrid incremental sheet forming (ISF) processes (Göttmann et al. 2013), efficient 3D-ultrafast laser ablation (Finger et al. 2015), and new advanced weaving technologies (Gloy et al. 2015).

While concentrating on solving the dilemma between scale and scope (i.e., enhancing process efficiency and quality), there has been little research on integrating AMT into agile product development processes (Schuh et al. 2017a). Technical limitations and the systematic deviations between AMT and conventional manufacturing technologies (e.g., spring-back for incremental sheet forming or resulting microstructure for AM) restrict a wider use of AMT for minimum viable products (Schmitz et al. 2020).

AMT typically provides a new “freedom of design” (e.g., lattice structures by AM, functional surface structures by laser ablation, or complex patterns by 3D weaving), resulting in a multiscale problem. To adopt a product or component to specific functional requirements, thousands or millions of lattice or surface structures must be adopted to those requirements. Due to the increased design effort and the according lead time, the potential of such functional adopted multiscale structures could not fully be utilized today. Therefore, current international research focuses on the field of automated or generative design (Wu et al. 2015; Panesar et al. 2018; Hinke 2018).

18.3.2 Overview of Research Areas Within “Enablers and Tools”

As described in the first section, the concept of minimum viable products (MVP) is an auspicious approach to radically reduce development lead time while drastically increasing customer/user satisfaction simultaneously. To answer development questions with the aid of MVP, the respective MVP has to adequately represent the requirements derived from the research questions. In this context, MVP represents not only the product/component geometric or haptic design but all relevant functional and mechanical properties necessary for answering the development question focused on by a sprint (see Fig. 18.2).

The research field “Advanced Manufacturing Technologies” (AMT) focuses on the industrialization of AMT and its integration into agile product development processes. Additive and subtractive Digital Photonic Production (DPP) technologies like additive manufacturing (AM) and ultrafast laser ablation, as well as incremental sheet forming (ISF) or advanced weaving technologies for 4D textiles, enable

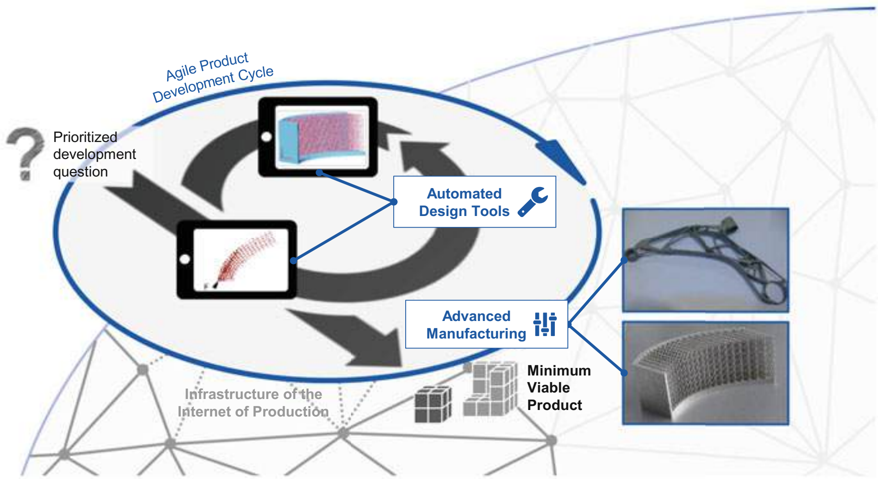

Fig. 18.2 Conceptual overview of automated design tools and advanced manufacturing for agile product development

the efficient and rapid production of small lot sizes and complex geometries. Furthermore, such technologies allow the direct transfer of product ideas into physical MVPs. Thereby, these technologies enable agile product development in two ways:

1. AMT allows for the efficient and rapid realization of market teasers, feasibility studies, and functional prototypes in terms of MVP.
2. AMT enables the efficient series production of small lot sizes, a critical success factor for agile developed products – especially when it comes to the realization of product releases in small numbers.

Based on the digital material shadow and the digital production shadow, the focus is on understanding, managing, and reducing systematic deviations (e.g., microstructure, mechanical properties, or surface quality) of components manufactured with diverse AMT. Based on these findings, it is possible to evaluate different AMT in terms of applicability to develop a question-focused MVP. Due to the modelling and understanding with the aid of gathered data, the optimal AMT for MVP production can be selected considering the development question as well as time and cost. The intended integration of AMT into agile product development is based on the systematic management of deviations of the components by means of model and databased optimization of technology chains and process parameters. Selecting the optimal AMT concerning the development question becomes essential for agile product development. In combination with the respective minimum viability mentioned Sect. 18.2 and the understanding of the AMT processes, it is possible to allow databased selection of the respective technology to be used for producing an MVP. Therefore, evaluation, and selection of the appropriate manufacturing technology an IoP-based, interactive prototyping toolbox is derived, mapping the MVP requirements (e.g., geometric tolerance and mechanical properties of a security-sensitive car body component), the digital shadow of potential AMT from (e.g., geometric tolerance of ISF) and the digital shadow of resulting material behavior from (e.g., achievable microstructure of AM). Although AMT are promising for agile product development, there are still many technological limitations. In order to accomplish the intended industrialization and applicability of AMT the research in this the respective following section on enablers and tools focuses on enhancing the performance of advanced manufacturing processes (e.g., mechanical properties, surface quality, efficiency) and corresponding machine tools. The examples described in Sect. 18.3, are reduced spring-back of ISF components due to model-based CAD-CAM chains or increased flexibility of laser ablation machine tools due to new kinematic approaches based on machine learning. Data from the production process of MVP allows the continuous evaluation and adjustment of parameters for process optimization.

Beyond AMT for the efficient and rapid realization of MVP, another key enabler for agile product development are IoP-based automated, interactive, and networked design tools. These tools are integrated into the different sprint types (market development, engineering, and production of prototypes). Based on reduced models and model-based AI methods, these interactive tools should automatically design product or component geometries, respectively, geometric structures based on the material-specific digital shadow, the process-specific digital shadow, and continuously tracked data from production processes. The examples described in Sect. 18.3 are a design tool for algorithmic generation of lattice structures for AM and an AI-based design tool for Optical Systems Development.

18.4 Conclusion

As described, the Cluster Research Domain C (CRD-C) “Agile Product Development” focuses on the determination of processes, structures, as well as enablers and tools for agile product development for cyber-physical products. According to the current state of research, the previously described structure and the included research questions are elaborated in the following chapters of CRD-C.I and CRD-C.II. Within these chapters, research results and use cases are presented. In future research, the aim is to expand and scale the results obtained to date. Overall, the increasing importance of the topic sustainability will be taken into account for future research. The question of the influence of sustainability on agile product development will be addressed. Longer product life cycles, but more individualized products, are to be expected.

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Processes and Structures for Agile Product Development

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Abstract

The work stream CRD-C.I of the Cluster of Excellence Internet of Production focuses on the topic of agile product development in order to enable reduced lead-times as well as exceeded customer and user satisfaction in product development. The main emphasis of the research lies on the associated processes and structures. In the course of the first 3 years of the Internet of Production, answers to relevant research questions of agile product development were developed within and between the research areas of market development, organization, data and engineering as well as production of prototypes. This chapter presents selected focus areas and insights from these research areas.

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19.1 Introduction

The overall goal of agile product development is to enable a radical reduction of lead-times while at the same time exceeding customer and user satisfaction. In order to achieve this goal, procedural and structural elements of the conventional and plan-driven product development approach need to be questioned and adapted. The work stream CRD-C.I of the Internet of Production focuses its research on necessary processes, methods, and structures in terms of market development, data and engineering, production of prototypes, and organization. Thus, the following research questions structure the work stream: How should agile processes and methods be designed to support market development, data and engineering, and production of prototypes? How should agile organizational structures be designed and how can an agile culture be implemented? What are the data structures needed to eliminate semantical conflicts and latencies?

The Internet of Production differentiates between the three areas of market development, engineering, and production of prototypes. Accordingly, underlying procedure models are derived considering multi-perspective and persistent datasets. In this context, the systematic transmission of the advantages of agile software methods on cyber-physical products is addressed. The respective organizational structures in combination with an agile culture enable the realization of advantages. Finally, the processes are enhanced as the transparent exchange of data along the process erases latencies and semantical conflicts.

In the course of the first 3 years of the Cluster of Excellence Internet of Production, answers to the relevant research questions of agile product development were developed within and between the research areas of market development, organization, data and engineering, and production of prototypes of the work stream CRD-C.I. Research results were elaborated in short-term cycles and presented on a cross-research-areas basis. The following sub-chapters present highlights from the results of these research areas. The chapter closes with a conclusion.

19.2 Market Development

Product development is increasingly characterized by high volatility, uncertainty, complexity, and ambiguity of customer and market requirements – especially at the beginning of the development process. The optimal product concept is impeded by constantly changing customer requirements and technological evolution. In this dynamic environment, a lack of customer integration can be a reason why companies fail to achieve user acceptance. The research area market development addresses this by providing *data-based tools and methods* that help *explore and assess requirements* based on usage data or explorative studies and transform them into product innovations. Early stakeholder integration in the agile development process allows requirements to be met more precisely, reducing uncertainty, leap

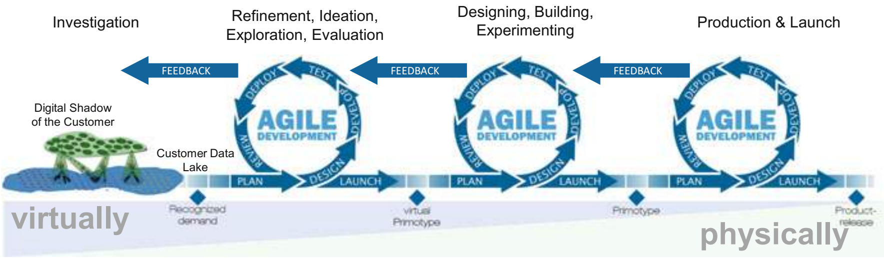

Fig. 19.1 Agile Process from virtual to physical state with iterations and development stages with feedback loops

time, and unnecessary product iterations. In order to achieve this, the research area market development investigates the following research questions:

- What is the process to perform a *non-hypothesis-based requirement assessment*?
- Which data, methods, and tools must be located in the process to identify and validate the requirements?

Figure 19.1 shows the sequence of such an agile development process with its stages, incremental outcomes, and iterative steps. The process is exemplary. Hence, stages and outcomes may be adapted according to the actual needs, and each stage may be implemented with its own agile development method.

The process starts with the recognition of potential demands. Focusing on the transition from a hypothesis-based to a data-driven requirement assessment, demands should be identified from the available data. The data is stored in a data lake, a collection of databases containing Digital Shadows for the product and the customer. Once a Digital Shadow has been generated, results and procedures can be reused for subsequent tasks. Thereby, Digital Shadows continuously improve with their usage since the underlying models are validated and extended with each additional experiment.

The Digital Shadow of the Product can be seen as more than solely a digital counterpart to a physical object, but also a virtual product with a particular set of properties that may further evolve into a physical product at later stages of development iterations. The Digital Shadow of the Customer, on the other hand, is the digital representation of the customers, whose usage data relates to the usage of a product and whose profile data provides insights about their preferences and behaviors.

After recognizing potential demands, each stage goes through its iterative development sub-process with a respective focus, resulting in an outcome. This outcome can be, for example, a concept, a prototype, or eventually the actual product. Results and insights from each stage flow back as new information into the previous stage as well as the data lake, indicated by the feedback arrows in Fig. 19.1. With that, the generation of feedback to the Digital Shadow of the Customer and the Digital Shadow of the Product at each development step is implemented as a mechanism in the process itself. Thus, creating an overall loop, integrating the Production Cycle and User Cycle into the Development Cycle.

At the early stages of the process, a product or demand may be handled entirely virtually. That means the intended improvement or new product is designed as a *virtual prototype*, which is meant to be tested and entirely deployed in a virtual environment. Developing in a virtual environment allows for preserving scarce (physical) resources. The strategic decision on what opportunity (i.e., demand) to follow postpones to a later point when more knowledge about the later potential products exists. Hence, reducing the uncertainty and complexity beforehand. With the progression of the process, each development stage enables a more and more physical implementation of the newly developed concept, thus gradually transforming the virtual prototype into a physical prototype.

19.2.1 Focus Area I – Data Types in Product Development

The main research questions of the research area market development establish a definite goal: the transition from a hypothesis-based to *data-driven decision-making* in product development in order to enhance decision quality and decrease decision latency. This section focuses on the foundation for this goal – data. Successful products are based on customer needs, actively expressed or latent. It is the task of the company to identify those needs and translate them into technical product requirements (Brettel et al. 2014).

In production, the analysis of process data has a long history due to structured data from sensors and clear targets (e.g., failure or no failure). For product development, however, a variety of data sources is useful, which makes automation of data processing and data analysis harder. This requires a standardized description of the heterogeneous data. This work for the Internet of Production focuses on a bottom-up approach to describe and structure data types and its implications on the digital shadow (Briele et al. 2022, Schuh et al. 2020).

Product development not only uses customer-centered data but also product-centered data, e.g., Social Media data, usage data, sales data and quality data, measurement data. The data types differ not only in their sources but also in their properties. Six main properties show the difference between those data types: subjectivity, degree of structure, degree of specificity, number of data points, update frequency, and cost (initial and running). This standardized structure helps to identify similarities and differences and to select the right data for the application.

One trend is the use of big data. With the use of embedded sensors in everyday objects like fridges, a high amount of data is recorded from a large population. Also, natural language processing enables the automated recording of text-based data like social media data. Both offer unfiltered and unbiased information about the usage of products and latent needs in the best case but require advanced data science methods and bear the inherent risk of unspecific data. Another trend is to join multiple data types to multiply customer insights. For example, joint use of both, customer- and product-centered data, offers an end-to-end description from customer needs to technical requirement that singular data types cannot.

The implications toward the digital shadow are manifold: Firstly, the gathering and storing of the data need to be tailored to each data type, and the access is determined by development cycles in product development. Secondly, the high number of decisions in product development prevents an easy automation of the data analysis. While at the beginning, the most important product features must be identified and ranked, they later must be specified exactly. Thus, every digital shadow is tailored to a specific decision in product development.

19.2.2 Focus Area II – Integrating the Digital Shadow into the Fuzzy Frontend of Innovation

One of the biggest challenges in product development is the question of which development activities the company should invest in. Since identifying and exploring the most promising development paths are usually highly complex and uncertain, they are also called the fuzzy front end of innovation (Harraf et al. 2015).

In the past, various methods and tools have been developed to generate knowledge and systematize the decision to manage the complexity and reduce the uncertainty. However, due to their contextual and time-related constraints, those methods and tools might not be fully applicable in the context of the IoP. This raises questions about how the Digital Shadow can be applied using existing tools or how these tools can be adapted to make the Digital Shadow applicable. On the other hand, each method and tool are based on underlying assumptions, which raises the question of whether data integration and automation are even desirable goals (Harsch et al. 2020).

Multiple methods and tools have been selected and structured, and each step has been analyzed for its constraints and underlying assumptions. Based on that, a potential level of *digitalization* has been assessed. Further, some methods have been empirically tested (e.g., Lead User identification using social and usage data) or have been already implemented as a digital tool (e.g., Outcome-Driven Innovation).

Moreover, several constraints influence the choice of *appropriate methods* and tools, forcing organizations to decide what method or tool to use and adapt them to each purpose. E.g., SMEs often do not have the capacity or prerequisites to acquire or analyze the necessary data, let alone build their own IoP. Such constraints limit the applicability of the theoretical Digital Shadow. *Decision support* is needed, which considers the respective goal of the endeavor and the available resources of the company. The insights gained from the analysis of the methods and tools are the basis for such a decision support tool.

In addition to the purely functional aspects, other hurdles can hinder the effective integration of the Digital Shadow – for example, the paradox of openness at the strategic level (Laursen and Salter 2014). While the commercialization of innovation requires protection, the creation of innovation often requires openness, or in this context, the release of one's own data into the data lake. That often leads to the consequence that many companies participate in open platforms but are not willing to share their data. As a result, any data-driven concepts such as digital shadows come to a standstill.

Another example would be the aversion to algorithms on the psychological or human level (Castelo et al. 2019). Data-driven concepts such as the digital shadow include automatic analyzes and artificial intelligence. However, the best artificial intelligence in the world does not bring benefits if there is internal resistance to accepting possible decisions or outcomes.

Therefore, by analyzing *innovation methods* and tools for the *systematic identification and exploration of the most promising development paths*, taking possible constraints and hurdles into account, theoretical and practical solutions for effectively integrating the Digital Shadow can be derived and developed.

19.2.3 Focus Area III – Human Systems Exploration with Tangible XR

The early involvement of users, usability experts, and other relevant stakeholders in the development process can help to reduce the uncertainty of customer requirements at an early stage. However, this can be difficult because the product is not in a usable state. One solution to explore and evaluate possible interaction concepts of a product before it is physically developed is the tangible mixed reality (Tangible XR) (Ays et al. 2018; Flemisch et al. 2020; Meyer et al. 2021).

In the IoP, this is investigated for the *multimodal prototyping* of a car door opening mechanism. The prototype contains both physical and virtual components. The physical mock-up consists of a frame made of aluminum profiles, which are assembled into a doorframe. This doorframe is connected to a virtual simulation environment via a force feedback device. The user feels the forces of the device as passive resistance when opening the door. The parameters of the device, e.g., forces or damping, can be adapted in real-time. In addition to the real haptic impression, the user perceives the visual impression of the door in a virtual environment (Schuh et al. 2021).

Through this approach, Tangible XR addresses the tension field between virtual and physical development, shown in Fig. 19.1. The goal is to integrate physical components into the virtual prototype at an early stage. By doing this, more detailed feedback, e.g., on haptic product properties, can be obtained at an earlier stage. The possibility to modify parameters of the product prosperities in real-time also allows exploring new interaction concepts with users and other stakeholders. Thus, exploration is a method that cannot only be used for human systems design, but also for *non-hypothesis-based requirements* assessment (e.g., Flemisch et al. 2021). The data obtained can be used to identify customer requirements and thus reduce uncertainties in the agile development process.

19.3 Organization

The overall goal of *agile product development* is to enable a radical reduction of lead-time while at the same time exceeding customer and user satisfaction. To achieve this goal, procedural and structural elements of the conventional and plan-driven product development approach need to be questioned and adapted. In order to drive agile product development comprehensively, several research areas need to be addressed. The research areas of market development, engineering, and production of prototypes address the derivation of the underlying procedure models that need to be defined and maintained to drive agility. However, an overarching perspective with a strategic focus on how to implement agile structures and values within the entire organization is essential to drive an "*agile transformation*."

The research area organization focuses its research on agile *working structures* and teams as well as the implementation of *agile culture* to provide a holistic and strategic view on how to effectively implement organizational agility. First and foremost, the necessary members within an agile development team must be defined. As an example, the so-called "Voice of the Product" exists in terms of a group of project managers, who hold the overall responsibility. As another example, *cross-functional team* members participate depending on the sprint target, process type, and targeted viability of the sprint outcome. In conclusion, the combination of hierarchical organization with lateral working structures can be a solution, as it supports direct communication (lateral structure) as well as instant decision-making (hierarchical organization). Next to the agile working structure, culture and acceptance are important for the transformation towards an agile company. Management principles, values, and working environment present three main factors whose adaption becomes necessary to implement agile processes. Basic mechanisms within this context exist within several management theories (e.g., team theory, lean management, flexible organization, system-oriented management). After the mechanism abstraction, their connection to a theory for the transformation towards an agile company is possible. Furthermore, the analysis of behavior patterns gives further insight into an agile culture. In this context, acceptance profiles, which are derived in CRD-D, allow further organization design.

The research field organization has derived several best practices and recommended actions to effectively establish organizational agility. Selective key insights, which could be organized into the focus areas of (1) Culture & Mindset, (2) Organization and Team composition, and (3) Strategy and Leadership, are presented in the following. The overall framework is illustrated in Fig. 19.2.

19.3.1 Focus Area I – Culture and Mindset

Agile cultures require a new understanding of leadership. This new form of leadership is based on the separation of technical and disciplinary leadership and responsibility. Separating technical and disciplinary responsibility allows managers to concentrate on individual strengths and simultaneously focus on actual task

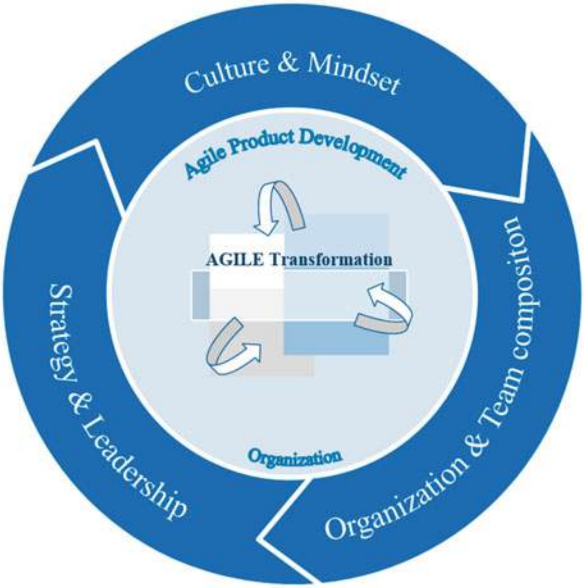

Fig. 19.2 Organizational agility framework: Selective key focus

requirements. This way, both the development of individual employees and teams as well as the development of the product can be driven most effectively, allowing to increase employee satisfaction while fostering motivation, efficiency, and creativity. Managers that focus on agility understand the need to replace a culture of "command & control" with a focus on personal responsibility, commitment, and feedback. This also allows key decision-makers to regularly exchange ideas with their teams and to inspire, encourage, challenge, and learn from their employees. Agility requires a *corporate culture* that enables a balanced and equal focus on the development of its products as well as its employees.

Furthermore, agile companies create corporate cultures that allow them to overcome "*completeness paranoia*" and rigorously facilitate output-oriented work methods. Embedding an *agile mindset* within the company requires the departure from previous premises and the need to let go of old structures and pieces of wisdom. Especially in the early phases of product development, agile organizational cultures foster approaches of proactive trial and error, the permission to make and learn from mistakes, and an appreciation of "work in progress" that allows for iterative and quick adoption along the way. Development teams should be able to focus on essential features in the early stages of development and present interim results that do not have to be perfectly detailed and complete. Managers that try to implement agile cultures need to focus on building trust and cooperation among team members and need to act as role models when it comes to exchanging that allows for mistakes, failures, and mutual learning. This way, companies can establish a results-oriented working and product development style that allows for quick initialization and adaption, leading to shorter time-to-market and better and quicker fulfillment of changing *customer requirements*.

19.3.2 Focus Area II – Organization and Team Composition

To ensure that companies can benefit sustainably from an agile culture and an agile mindset, this must be embedded within the *organizational structure* of the company. Thus, organizing processes and frameworks can be set up and established in particular. For this, training on agile fundamentals in form of agile concepts, *methods*, and *processes* is indispensable. However, these should not only be made available to multipliers who are to disseminate them within the company but should also be made available to as many employees as possible at the operational working level. In addition to relying on a bottom-up strategy, it is important to teach management how to exercise agile leadership. In this way, a top-down approach can also be implemented and the commitment of management to an increased establishment of agility in the company can be manifested at an early stage. Management support is one of the most frequently mentioned success factors for kick-starting the agile transformation to this end. Since the introduction of agile product development involves a great deal of effort, it must not be an end in itself. To be able to fully realize the potential of agile development, holistic implementation is required in all relevant divisions of the company.

In addition to the organizational embedding and the training of the employees, the *team composition* is particularly important to establish agility in the company. The composition of the team is one of the most important decisions to be made in the course of a project, as a suitable mix of experience, competencies in product development, creativity, and marketing competencies must be found. Therefore, a cross-functional team is required for mastering all challenges within the team and being responsible for the project from the beginning to the end. Especially, cross-functional teams can be enabled organizationally to identify and communicate problems. To ensure the development of solutions to the identified problems within the team in a targeted manner, a dedicated transfer of responsibility to the team and a suitable process for solving problems are required in addition to the successful cross-functional team composition. Both are part of the agile transformation and therefore part of the previously mentioned training. In order to keep the performance of the team on a constant and high level over the project duration, a long-term team composition is to be strived for and the composition is not to be changed, if possible, thus the work mode and the communication culture can be maintained. Since this process may take some time, a dedicated responsibility assigned to the team and its results is necessary to increase the commitment within the team to achieve good results.

19.3.3 Focus Area III – Strategy and Leadership

To ensure a sustainable and long-term establishment of the agile culture in the company, it must also be embedded in the *corporate strategy*. Even though the approaches of agile product development and classic plan-driven development are often perceived as incompatible, the integration of agile culture into corporate strategy is not a binary decision. Companies therefore often decide to combine approaches of agile and plan-driven product development and thus benefit from the advantages of both perspectives. In particular, the systematic processes of plan-driven development and the more reactive working method of agile development are to be mentioned here. There are different levels of integration for the combination of agile and plan-driven approaches in product development, from the integration of selected agile methods to the agile working between project parts or at the beginning of a project in the early development phase. The extent to which the agile culture is embedded in the company's strategy must therefore be decided by the management and is dependent on the company-specific boundary conditions. Regardless of the specific form of the agile transformation, embedding it in the corporate strategy helps to increase visibility and commitment within the company. This is particularly advantageous for a longer *transformation process* in which numerous challenges have to be mastered at the beginning. Nevertheless, the support of the top management is essential to overcome these situations. As already mentioned in the Sect. 19.3.2, the commitment of the company's management is important in the implementation of an agile culture.

To foster top management support, it is advisable to promote institutionalization with a board member. To this end, a more intensive commitment of the board to the agile strategy is achieved and experienced. Furthermore, clear reporting and decision-making paths must be established to avoid uncertainties in decision-making within the agile team, which should make everyday decisions as independently as possible so that bureaucratic and hierarchical hurdles can be avoided. To strengthen the idea of leadership in an agile organization, the technical and disciplinary management should be separated, as can be successfully implemented by means of a *product owner* and *agile manager*. Regular exchange between the managers and the operational teams is thus becoming increasingly important. Overall, embedding agile thinking in strategy and management can enable the company to allow both managers and employees to concentrate on the essential tasks and prevent micromanagement. This can only be achieved by breaking up previous structures and transferring responsibility for decisions to the agile teams.

19.4 Data and Engineering

The research area data and engineering addresses the research questions "How should agile processes and methods be designed to support market development, data and engineering and production of prototypes?" and "What are the data structures needed to eliminate semantical conflicts and latencies?"

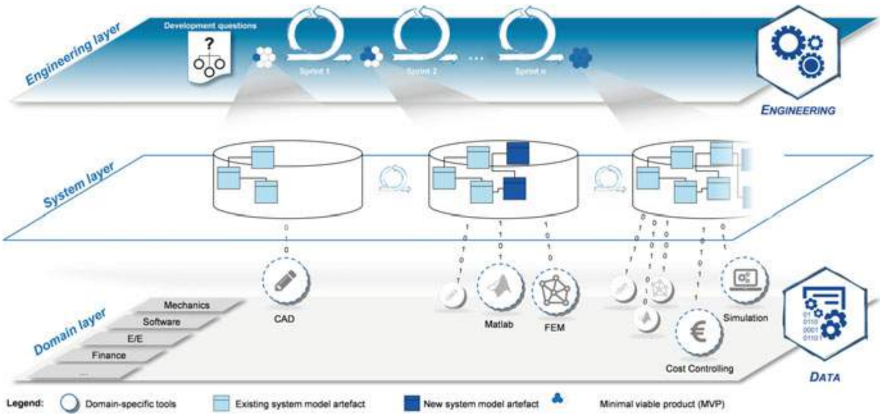

Fig. 19.3 General framework of the research area data and engineering

The ever-increasing demand for variant creation and engineering change requests (ECRs) results in the need for flexible product development and production. This entails agile development and manufacturing of products down to batch size one while simultaneously dealing with the growing complexity of the fabricated systems. An agile process includes the automation of tasks, which in turn means that engineering artifacts must be available in machine-processable form. In this regard, the approach of *model-based systems engineering* (MBSE) can be applied, where formalized and structured models represent the central development artifacts. A central element in many MBSE approaches is the so-called *system model*, which describes the overall structure and behavior of the system. It serves as single-source-of-truth in the development process and is often established using the systems modeling language (SysML).

The ability to perform ECRs adaptively while maintaining data consistency and avoiding media disruption is central to an agile yet stable production line. However, MBSE is basically characterized by a strong frontloading. Thus, the challenge is to synchronize *agile* development and model-based development. Overall, MBSE is a promising opportunity for agile product development and production. It offers various opportunities, such as virtual prototyping or digital twins. The integration of MBSE into agile product development is illustrated in Fig. 19.3 and represents the objective of the research area *data and engineering*.

The target is the synchronization between agile development and MBSE via the systematic construction of system models, including the consistent connection of domain-specific development tools. In the following, three focus areas are explained, focusing on the necessary processes, methods, and infrastructure to introduce an agile development through MBSE.

19.4.1 Focus Area I – Synchronization of Agile Development Processes and System Engineering Processes

To build a system model at the beginning of the development process, an initial time investment is substantial as the modeling is a complex procedure. Furthermore, there are numerous uncertainties about the relevant requirements and artifacts to be implemented. Therefore, an iterative approach should be applied to transfer agile principles to system modeling. Within the research area data and engineering, an approach for *iterative system modeling* in agile product development was developed. It focuses on defining the relevant design parameters, which need to be considered in a sprint (Riesener et al. 2019). Furthermore, the methodology developed enables the determination of a specific selection of development tools that are required to answer the questions arising from agile development and considers the previously identified design parameters (Riesener et al. 2021).

In an agile product development process, the development proceeds in defined sprints in which specified increments are realized. The evaluable increments provide the answer for the development questions to be clarified within the development process. They are composed of various product-oriented design parameters such as height, length, weight, and material. Thus, it is necessary to evaluate to what extent the design parameters contribute to the resolution of uncertainties and identify the design parameters that fit together into a validatable increment due to their technical relations. Based on this, *sprint-specific prioritizations* and selection of technical design parameters can be conducted. These product-oriented design parameters need to be transformed into system-model-oriented design parameters to build up the corresponding system model. The structure of the system model is discussed in detail in the following focus area.

As the system model can only provide information to answer the development questions, it is relevant to integrate development tools, which are able to process the information to support answering the development question of a specific sprint. Different domain-specific tools can be used for this purpose. Within the developed methodology, the focus initially lay on the integration of computer-aided development tools (CAx). A developed tool description framework can be used to formally describe input and output information of the respective development tools, and therefore, it provides the basis for the evaluation of question-specific toolsets. By linking the framework to the design parameters, which provide the respective input information, it is possible to evaluate which development tools are best suited to elaborate the respective inputs (design parameters) and generate corresponding outputs. As a result, an optimized set of development tools for each sprint can be derived in order to answer specific development questions. The first focus area presents an approach for synchronizing agile development processes and system engineering processes, especially to use CAx development tools iteratively in the context of system modeling. In the following focus area, the structure of system models, as well as the opportunity of handling ECRs, are specified.

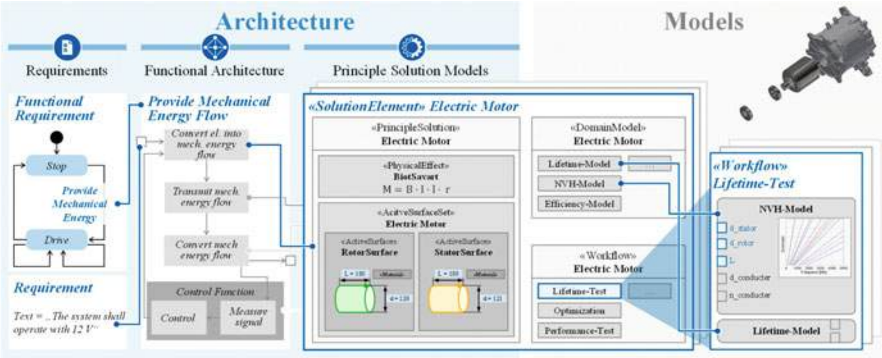

Fig. 19.4 Overview of the SysML system model architecture and linkage to domain specific models shown for the example of an electric motor (Jacobs et al. 2022)

19.4.2 Focus Area II – The System Model as an Enabler for Rapid Engineering Change Requests

A successful implementation of MBSE approaches requires a *function-oriented* and model-based system architecture, the classification of domain expert models, and the linkage of the system architecture and expert models and calculation workflows (see Fig. 19.4) (Jacobs et al. 2022). The system architecture is represented by a SysML system model and consists of requirements, functional architecture, principle solution models, and solution elements (containing principle solution and domain models). The presented methodology allows linking all system elements on a parameter level with each other. Similarly, the domain models (e.g., MBS, FEM) can be linked to the solution elements of the architecture model. This generates a high level of data consistency from requirements over functions to solutions.

The ability to perform rapid ECRs is a major premise to be able to increase agility in future development processes. MBSE approaches as described above promise to provide an engineering environment in which rapid ECRs can be enabled. A first approach on how a SysML system model can enable rapid ECRs was developed (Meißner et al. 2021). The focus of this approach lies on the linkage of requirements, system parameters, and domain models. First, the system parameters, which are needed to verify the requirement satisfaction, are identified and linked to the respective requirements. Then suitable domain models determining the identified system parameters have to be linked to these system parameters in the SysML system model. This allows an automatic check of whether a requirement is satisfied or not. In case of unmet *requirements*, the system parameters responsible as well as system parameters relevant to be changed can be identified. For specific test cases that consider multiple system elements and require different models to be executed, model workflows can be implemented within the system model to automatically check these scenarios. Therefore, feedback loops can be drastically shortened.

In focus area II, the general structure of the system model (Jacobs et al. 2022), as well as an approach to use a *SysML-based system model* for the execution of rapid ECRs (Meißner et al. 2021), was presented. The following focus area elaborates on flexible parameter extraction from such models to enable this linkage.

19.4.3 Focus Area III – Information Distribution and Change Propagation over Heterogeneous Engineering Artifacts

To harness the benefits of *integrated system modeling*, the different domain-specific models have to be interconnected. This requires extracting relevant parameters from models and synchronizing these with parameters of other incorporated models. As systems engineering is highly interdisciplinary, this poses a challenge as terminology, and thus, the distinct domain-specific models are highly heterogeneous. Standardization and exchange formats help to bridge this gap but only provide a mere foundation for data distribution. Connecting parameters of relevant models enables tracing information across the heterogeneous tooling landscape (Dalibor et al. 2019a) and validating domain-specific configurations in the context of the overall system under development. To support rapid ECRs while simultaneously ensuring product quality, automation of this process is essential. Whenever a developer makes a contribution to the system, a *continuous integration pipeline* is triggered to check whether the changes are feasible with respect to the existing artifacts.

The general notion of automation and continuous integration, thus, perfectly matches the problem of agile MBSE by integrating engineering models of various domains. Here, these concepts are applied to the broader field of systems engineering, resulting in a huge challenge of connecting models and distributing information in a semantically sound way. Furthermore, in contrast to software engineering, the engineering models in MBSE generally do not appear as plain text artifacts but are often encoded in a carrier language (such as XML), making it harder (for humans and machines) to detect the impacts of a change. In the worst case, the engineering model is only available as a binary file, requiring an application programming interface (API) for proper access to parameters.

Thus, *information distribution* and change propagation require the underlying continuous integration platform to handle the different artifact types, being able to extract parameters independent of the encoding. As new models and model types can constantly be incorporated during development, when synchronizing agile development processes and MBSE, an underlying framework that handles parameter extraction must be equally extensible. In a respective approach, models must be parsed (in the case of textual formats) or (for binary artifacts) accessed via an API. For each model type, an associated module can be defined in the framework that can read and reintegrate parameters from the models, enabling standardized information interchange. These modules serve as a communication interface between the domain-specific syntax of the models and the general exchange of data (Dalibor et al. 2019b). To enable this information distribution, the control flow of included tools and the data flow between the models must be specified. In software engineering, this is handled by building scripts, such as *Makefiles* or *Gradle*. While additional, specially tailored solutions for systems engineering exist, which provide more accessible user interfaces (especially for non-programmers), the basic concept remains the same. However, these frameworks need to be able to run in batch mode, operating without manual input, to ensure automation in the overall data exchange and validation process. Combining these approaches of a continuous integration platform for MBSE with seamless integration of interdisciplinary engineering models enables continuous data transfer and facilitates agile development.

19.5 Production of Prototypes

The rapid change of product requirements (Engineering Change Request ECR) in the agile development process poses new challenges for technology planning in the design of *manufacturing systems* for series production. In particular, the interface between engineering and *technology planning* is significant due to the need for rapid and efficient analysis of technological and economic effects of ECRs on manufacturing. In addition to ECRs, the increased dynamics and agility of the product development process result in new challenges for the *design and dimensioning* of manufacturing systems. However, there are also numerous opportunities to meet the existing challenges as well as the increasing cost and time pressure through the *production of prototypes* for information acquisition and validation of planning. To exploit the potential of increased agility as well as the generated knowledge, it is necessary to understand the cause-effect relationships at the interfaces of engineering, technology planning, and the design of individual processes. Prototypes are a particularly valuable source of information in this context, as they are exposed to the actual environmental influences of physical production and thus provide valuable information for process design in addition to validating simulation and planning results. The research area production of prototypes aims to use the information generated by prototype tests to develop *models and methods* for optimizing and increasing the efficiency of product development processes and to analyze the cause-effect relationships at the interfaces of engineering, technology planning, and process design. For this purpose, four focus areas were defined, which attack the different interfaces to analyze and model the interactions. In the following, the focus areas and the current research results are described.

19.5.1 Focus Area I – Engineering Change Requests in the Product Development Process

Engineering Change Requests (ECR) in the product development process repeatedly present manufacturing companies with economic and technological challenges, as they lead to time-consuming and cost-intensive change measures, especially in the late phases of the development process. To meet this challenge, a software prototype was developed that analyzes the impact of design changes in terms of technological feasibility and forecasts the economic impact based on a volumetric cost calculation. This enables the engineering department to get direct feedback on design changes, thus achieving significant time and cost advantages in the development process and increasing the competitiveness of companies. Furthermore, the tool offers the possibility to derive corresponding prototype tests by comparing the technological feasibility and the deviating product requirement profile to generate missing information.

19.5.2 Focus Area II – Agile Ramp-Up Production

Due to the shortened product life cycles and the increased time and cost pressure of efficient production, the pressure on manufacturing companies to carry out more ramp-up productions in ever shorter periods of time has increased (Rey et al. 2019). Currently, however, the time and cost targets for ramp-up productions are not achieved, which results in competitive disadvantages for manufacturing companies. The failure to achieve these targets is due, for example, to production-related engineering and manufacturing changes (E/MCRs), which lead to time-consuming and cost-intensive changes during the ramp-up production (Kukulies and Schmitt 2018). The idea of current research work is to transfer the methodology of agile product development to the ramp-up production and to integrate it into product development in accordance with the hypothesis that E/MCRs in the ramp-up production correspond to the same problems as the changing customer requirements in the product development process. This is referred to in the following as *agile ramp-up production* (Bergs et al. 2021). The aim is to use the increased agility and the knowledge generated from the prototype tests to identify E/MCRs at an early stage and to stabilize the ramp-up production in a targeted manner. Due to the *uncertainty* that thus prevails during the ramp-up production, it is necessary to know exactly where which uncertainties exist and what effects they have. Various models and methods have been developed for this purpose as part of the research work in the Cluster of Excellence IoP. Based on the modeling of uncertainties, a prognosis model was developed, which enables the prognosis, evaluation, and prioritization of E/MCRs based on the modeled uncertainties. Expanding on the results, another model was developed that enables the optimal derivation of prototypes to be manufactured for early reduction and validation of E/MCRs. Based on these models, a methodology was then developed that supports companies in technology-specific decision-making, considering product and process maturity as well as the probability of use of manufacturing technologies in the series manufacturing system in agile ramp-up production.

Furthermore, research was also conducted into how the manufacturing *process sequences* to be designed in the agile ramp-up production can be optimized economically (late ramp-up phase). The aim here is to design the manufacturing processes (definition of process parameters) according to the available information basis so that a *cross-process*, economical optimum is achieved and at the same time the required component characteristics for the final component (quality) are met. For this purpose, however, both economic and technological *interdependencies* between the different manufacturing processes have to be modeled. The concept developed for this purpose provides for the individual processes to be represented by meta-models, which approximate known system states, and are linked to corresponding transfer variables (intermediate component state characteristics). The advantage of *meta-modeling* is that these models can be quickly extended and detailed by further data from the ramp-up production (e.g., from prototypes or analogy tests). The linked meta-models make it possible to evaluate the effects of individual process parameters on final component characteristics and to predict component characteristics for different designs of the process sequence. Parallel to this, an economical evaluation of the manufacturing process sequence is carried out, in which the costs of the individual processes are determined as a function of the respective process design and transferred to a higher-level evaluation model. These two variables (predicted component characteristics and economical result) then form the input variables for a metaheuristic optimization approach (selection due to non-linear correlations and binary variables) to identify the most suitable process parameter combination. This result is then evaluated according to the information basis so that the meta-models are increasingly validated and improved by prototype tests within the agile ramp-up production.

19.5.3 Focus Area III – First Part Quick, Right, and Productive

The importance of detailed process simulations as a basis for quick and correct process design of manufacturing processes is undisputed. Extending existing simulation approaches through increasing networking and data availability can overcome the barrier to flexible, cost-efficient *prediction of manufacturing processes* caused by data-driven models with higher accuracy. For a quick and correct design of milling processes, knowledge about expected process forces is of great importance. The calibration of existing simulation approaches is time-consuming and transferable only to a limited extent due to the complexity of manufacturing situations (Altintaş et al. 2014; Grossi et al. 2015). The Internet of Production creates the possibility of a *worldwide laboratory approach* through cross-domain, continuous data availability down to the machine level: Every production situation is recorded and documented by measurements. On this basis, the target is to quickly adapt known physical relationships to the current situation as well as to extract and quantify previously unknown relationships as new knowledge from the data. This hybrid combination enables manufacturing simulations to be used broadly and validly in the long term, so that processes can be designed quickly, correctly, and productively up to *prototype production*.

Three elementary steps are derived to achieve the target: In the first step, all cross-domain data along the product creation chain (CAD, CAM, manufacturing, and quality data) are automatically contextualized based on a digital shadow of the manufacturing object (Brecher et al. 2021). The basis is a material removal model in the area of manufacturing simulation, which, based on the designed or driven NC path, compares the material to be removed with the data measured at this time contextualized (live data: positions, torque-forming currents of the spindle and axis, spindle speed, process forces from a spindle-integrated force sensor; meta information: tool, NC block, workpiece and tool geometry, manufacturing feature, required quality features from the design). As a result, the data plane is transferred from the time domain to a location domain, which forms the basis for the *digital shadow*.

In the second step, the digital shadow is combined with known physical cause-effect relationships. Thereby it is possible to define each manufacturing situation as a so-called *behavior cluster* based on the cross-domain data. A behavior cluster forms a delimited multivariable data domain. Within this behavior cluster, manufacturing conditions are similarly based on the contextualized multivariable data. Physical effect relationships such as the parameterization of known, empirical force models as the Kienzle model, shown in Brecher et al. (2021), can be quickly parameterized due to the contextualized availability of the data within the current behavior cluster. In Brecher et al. (2022), the authors show the results of a cluster-based calibration process of empirical force models. If this behavior pattern is recognized via the available data exchange from planning to production within the manufacturing design, the stored parameterized empirical process force model can be used to estimate valid forces. Over time, as more manufacturing situations become available based on the data, a cluster space will be achieved that can predict potential impacts from ECR on the overall manufacturing process based on valid relationships.

In the third and final step, the target is to *extract the knowledge* implicit in the data with respect to manufacturing behavior using *AI-based methods*, to quantify it. The key advantage of the global laboratory approach through networking and the associated continuous data availability captures complex situations representing behavior that is not represented by conventional physical contexts. Based on the new insights extracted by data-based approaches, the previous process simulation can be further improved. For this purpose, the previous cluster-based modeling of physical contexts will be extended to a holistic *hybrid model structure*. As soon as the prediction of the process forces deviates via the cluster-based approach in the second step, this deviation is intercepted via an artificial neural network (ANN), which searches for correlations from the deviations in the data as a basis for quantifying unknown correlations. The authors show in Brecher et al. (2021) the impact of unknown correlations on process force during tool breakage. The deviations in prediction and measured force have been continuously processed by the network structure. This processing shows the potential of the ANN structure to represent other influences, such as here the vibration influence of the machine structure and its influence on the process force, in addition to the valid models in the cluster. As a result, such a network structure provides the basis to determine quantitative relationships in the long term. Current and future work uses AI-based algorithms such as LIME to quantify these new findings and make them available to process simulation.

19.6 Conclusion

In the first 3 years of the Cluster of Excellence Internet of Production, answers to relevant research questions of agile product development were developed in the research areas of the work stream CRD-C.I. Focus areas of these research areas and central results were presented in this chapter.

The research area of market development dealt with several questions on an abstract theoretical level as well as on a practical level. By making adequate use of the digital shadow within product development and by enabling design and deployment in a virtual environment, different ideas and concepts can be tested quickly. The research area intends to create at least a semi-automated, continuous, and iterative process of requirements elicitation while conserving resources. The research area of organization identified agile values in corporate culture, employees, organization, structures as well as strategy and leadership as the basis for success in dynamic and uncertain environments. Disruptive market changes, technological changes, and environmental shocks require companies to constantly rethink, react, and reinvent. The research area of data and engineering showed that systems engineering is a promising enabler for agile product development. Within the research area, a function-oriented and model-based system architecture as well as an approach to select relevant design parameters and development tools are presented. Furthermore, the integration of models in a fully automated continuous integration platform is described. The research area of production of prototypes provided a methodological and technical overview of the procedure for exploiting the potential of data-driven approaches to increase flexibility in prototype production due to agile product development. Due to the availability and exchange of data from product development to technology planning, detailed production planning, and manufacturing, new relationships can be extracted that have the potential to boost an agile and fast technology and process ramp-up in terms of expected effects, quality, productivity, and costs. Further research results will be the content of future publications of the Cluster of Excellence Internet of Production.

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Enablers and Tools for Agile Product Development

20

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Abstract

Today's industrial world is characterized by ever-shortening product development cycles and increasing degrees of product individualization which demand tools and enablers for accelerated prototyping. In addition, the existing uncertainty in the product development cycle should be reduced by involving stakeholders as early as possible. However, should an engineering change request (ECR) be necessary in the product development cycle, a fast iteration step into production is inevitable. The methodological description of such an ECR in the product development cycle is described in the previous chapter. Together with researchers from the Internet of Production (IoP), information from the product development process will be transferred to the digital shadow established in the IoP. The digital shadow collects information from all areas of the product lifecycle and provides it to the appropriate departments, adapted to the corresponding task. To tackle this challenge, a new type of product development process, the method of agile product development, is applied. Within the Enablers and Tools project, the development of various advanced manufacturing technologies (AMTs) for agile product development are at the forefront of the work. The enablers and tools are further developed with the principles of agile product development. They also serve to map the

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requirements for rapidly available and specific prototypes which are used to answer specific questions that arise during the product development cycle. To answer these questions, the concept of the Minimum Viable Product (MVP), an approach to reduce development time and increase customer satisfaction, is introduced and applied to all development tasks.

20.1 Introduction

Manufacturing companies continue to account for a high share of added value in Germany (Statistisches Bundesamt 2022). At the same time, companies are dependent on stable framework conditions. Changes in the framework conditions, e.g., due to changed value chains, rising raw material prices, or changes in consumer behavior, pose particular challenges for manufacturing companies (Brecher et al. 2017). In this context, sustainable corporate success is only possible through innovative products due to global competition (Schuh et al. 2017). To meet this challenge, flexible production processes and fast and efficient product development are required (Brecher et al. 2017).

To establish faster product development processes, the Enablers and Tools for agile product development subproject is investigating how the principles and methods of agile product development can be transferred to manufacturing companies. Agile product development methods are characterized in particular by the fact that uncertainties in the product development process can be reduced at an early stage through the early involvement of stakeholders. The new role of prototypes, in which prototypes are to answer specific questions in the product development process, also serve to reduce the uncertainty in the product development process. In this context, the subproject investigates how the maturity and execution level of prototypes can be determined in order to be able to answer specific questions (Schuh 2017).

For the meaningful and rapid production of these prototypes, enablers and tools are needed that can produce prototypes quickly and under the given boundary conditions. One major focus of the project is the further development of so-called advanced manufacturing technologies (AMTs) and how AMTs and data acquired from prototyping technologies can be used for agile product development. The second focus is the use of all relevant data from production and material to determine the minimum viability of a product prototype as well as to select, adapt and improve the respective prototyping technologies. In the long term, all relevant data provided shall be integrated into automated and interactive design tools to support continuous stakeholder integration as well as latency elimination for agile product development.

The following section describes the state of the art in agile product development and AMTs. Subsequently, the AMTs investigated in the subproject, such as 4D-textiles, additive manufacturing or robot-based laser material processing and interactive tools such as the automated design of optical systems, are presented.

20.2 State of the Art

Agile process methods are adaptive approaches originally used in software development and are characterized by an iterative development process. In each cycle with a defined length, increments are generated and validated by the customer. The strong involvement of the customer enables the development process to react proactively to new requirements. The development process is characterized by informal communication (Goll 2015). These methods aim to counteract the deficits of a requirements analysis at the beginning of a development project and allow an earlier usage of preliminary versions of the (software) product (Sommerville 2010).

The basis of agile process methods is the “Agile Manifesto” which defines four guiding values and 12 principles to aid implementation of agile methods into development processes, accepting the limited plannability of complex processes (Highsmith and Fowler 2001).

Defining characteristics of agile methods are (Sommerville 2010):

- **Flexibility and transparency**: Processes are designed efficiently and superfluous work steps are avoided as far as possible
- **Focus on people**: Processes are aligned according to the people involved and their capabilities. Developers work independently in close cooperation and are freed from strict procedural requirements
- **Involvement of the customer**: The customer is regularly involved in the development process. The customer’s task is to review the development process and help shape the further procedure
- **Accommodating change**: Changes are welcomed and actively addressed by developers
- **Iterative development**: The process is characterized by recurring activities
- **Incremental delivery**: Functional product increments are delivered to the customer at regular intervals. New requirements for the product are implemented with each delivery

In comparison to conventional development methods, the development cycles and the lead time to a marketable product are shortened significantly and the customer can intervene early since deviations between understanding of customer and developing team are detected at an early stage (Sommerville 2010). After each iteration cycle, the customer has a potentially applicable prototype. The Minimum Viable Product (MVP) is usable by early customers who can provide feedback for further product development.

Advanced manufacturing technologies (AMT) such as additive manufacturing (AM) allow an efficient transformation from digital design data into physical products and present a growing field of international research (Behera et al. 2013). Especially metal AM is of growing interest and several international research groups are working on this topic (Baumers et al. 2016; Zaeh and Ott 2011). While focused on solving the dilemma between scale and scope, i.e., enhancing process efficiency and quality, there is very little research on integrating advanced manufacturing technologies into agile product development processes. Technical limitations and the systematic deviations between AMT and conventional manufacturing technologies (e.g., spring-back for Incremental Sheet Forming or resulting microstructure for AM) restrict a wider use of AMT for functional prototypes.

Advanced manufacturing technologies typically provide a new "freedom of design" (e.g., lattice structures by AM, functional surface structures by laser ablation, or complex patterns by 3D-weaving) which results in a multi-scale problem. To adopt a product or component to specific functional requirements, thousands or millions of lattice or surface structures must be adopted to these requirements. Due to the increased design effort and the according lead-time, the potential of such functional adopted multi-scale structures cannot be fully utilized today. Therefore, we currently face a growing international research in the field of automated or generative design (Panesar et al. 2018; Wu et al. 2015).

One way of implementing agile techniques from software development into physical product development involves recording the work steps in the previous product development and defining suitable agile techniques as a replacement model in each case. Product development is carried out in an agile manner using the substitute models and finally merged into a complete process model (Kantelberg 2018; Klein 2016). Step 1 is used to capture the original product development process to identify the activities, decisions, and interactions of the stakeholders in the individual development steps. The development sub-steps are decomposed to define their modes of action based on processes, activities, tools, and roles. In step 2, a suitable agile technique such as Scrum is selected. The procedure is divided into processes, activities, tools, and roles, analogous to the previous product development process. In step 3, the processes, activities, tools, and roles of the two product development processes are transferred from the previous to agile product development in tabular form. Activity and decision maps as well as profiles of the agile techniques can be used as an aid. Agile submodels are assembled to form the rough concept of the workflow for physical product development (step 4), and product development is carried out in an agile manner using the developed concept (step 5) (Kantelberg 2018; Klein 2016).

By applying this general workstream, agile techniques can help enable a faster and more efficient product development process in the physical world. In the following chapters, examples of suitable AMTs and possible applications in the context of agile product development are presented. For each AMT, usage and integration of the technology and data acquired during manufacturing in agile development environments is explored. Also, the use of relevant data from production and material to determine the minimum viability of a product prototype as well as to select, adapt and improve the according prototyping technologies is investigated.

20.3 Contributions

20.3.1 Innovative Kinematic Systems for Laser Material Processing

In recent years, lasers have been established as a manufacturing tool with a wide variety of production processes, such as laser cutting, laser welding, or laser structuring in production technology (Hügel 2009; Poprawe 2005). Photonic technologies are also considered enablers for global environmental sustainability (BMBF 2018; Cochard and d'Humières 2019; Poprawe 2019). Furthermore, laser technology can be seen as a particularly flexible process that is suitable for the rapid and cost-effective production of prototypes and small series, also in the context of agile product development (Hinke 2018; Poprawe 2005). To apply laser technology in material processing, a relative motion between the laser tool and the material to be processed must be realized. This relative motion is typically implemented via kinematic systems that have been adapted from other manufacturing processes. Accordingly, these kinematic systems are not optimized for the requirements of laser technology and do not exploit the advantages of laser technology. Within the subproject, the suitability of new, innovative kinematic systems for laser material processing (LMP) is systematically investigated. With these new kinematics systems, LMP can be used as an enabler for agile product development in science and industry (Poprawe 2005).

Due to the non-contact processing of workpieces by laser radiation, no restoring forces act on the kinematic systems (Hügel 2009). Accordingly, the kinematic systems do not have to absorb these forces and can be designed to be less rigid than for other manufacturing processes, such as milling (Cen et al. 2016). As a result, flexible kinematics systems such as robots are suitable for LMP. The challenge here is that current, low-cost robotic systems do not meet the accuracy requirements.

The aim of the project is to investigate the potential of LMP with respect to new kinematic systems. For this purpose, concepts for new kinematic systems will be developed and their suitability for LMP will be investigated. The focus of the work is on increasing the accuracy of the kinematic systems. The kinematic systems are not developed to series production readiness, but the suitability of the systems in principle for LMP is investigated with prototypes via proof of concept. Currently, this is being investigated on two different prototypes.

The prototypes are themselves being developed using agile product development methods and each represents a Minimum Viable Product (MVP). For flexible 3D machining of components by using low-cost articulated robots (cobots) is investigated. A sensor system is being developed to accurately determine the Tool Center Point (TCP) state of the robot, see Fig. 20.1, left. The processing of large-area components by mobile robot systems is also being investigated, see Fig. 20.1, right.

Higher-level issues, such as how data generated during prototype development and use can be used, are also part of the work. The question of under what circumstances the components produced by means of the prototypes can be compared with later series components is being investigated as part of the work.

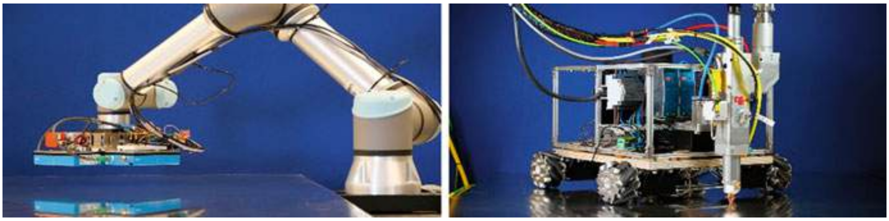

Fig. 20.1 MVP of a Tool Center Point sensing unit (left), MVP of a mobile robotic system for laser material processing (right)

Among other things, the following questions, some of which are of a higher order, will be addressed in the project:

- How can data generated during prototype development and use be applied?
- Under what circumstances are the components produced by means of the prototypes comparable with later, series-produced components.

Furthermore, the integration of the prototypes into the data lake planned in the Internet of Production (IoP) is being pursued .

20.3.2 Automated Process Optimization for the Production of Individualized Sheet Metal Parts

Flexible manufacturing processes, such as 3D printing, enable rapid product development and highly individualized products. A promising process to manufacture individual sheet metal parts in small quantities is incremental sheet forming (ISF), which has high geometric flexibility due to low tool binding. The process combination with stretch forming enables overcoming known process limits and significantly reduces the process time. In the part shown in Fig. 20.2, the global part curvature has been achieved by stretch forming, and ISF has been used for forming the cavities and other part features (Taleb et al. 2011).

The combination of the two forming processes results in a more complicated process planning (Bambach et al. 2009; Schmitz et al. 2020). At the same time, however, short development times and costs must be ensured, which is an important factor in efficient prototype design, especially for small quantities. For this reason, the Institute for Metal Forming (IBF) at RWTH Aachen University has been working on the further development of the planning chain for the digital automation and optimization of the process combination of stretch forming and ISF as part of the Cluster of Excellence.

The first step in process planning is the analysis of the part to be produced. For this purpose, the part surface is transferred to the planning tool and converted into a suitable three-dimensional mesh within the tool. With the help of the mesh, it can be evaluated whether the part can be produced with this process combination.

Fig. 20.2 Exemplary application part (inspection door Airbus A320), produced with the process combination of stretch forming and incremental sheet forming

After the first evaluation of the part, the process parameters, boundary conditions, and tool paths suggested by the tool are then automatically prepared for subsequent finite element (FE) simulations and transferred to the FE software via an interface. LS-Dyna from Livermore Software Technology Corporation is used as the FE solver for the simulation of the automatically planned forming process. Based on the automatic planning and simulation chain, an autonomous optimization loop was established with the help of an interface to the optimization program LS-Opt.

The optimization model can change the originally defined orientation of the part as well as the tool paths depending on the simulation result. Metamodels are used to optimize the process simulation and their predictive capability is iteratively improved until the model can predict an optimal parameter combination.

The developed automated planning and optimization tool can optimize the individual steps of the process chain by coupling CAD/CAM software with an FE solver.

By optimizing with the help of metamodels, various process parameters can be flexibly tested and evaluated automatically by the planning tool with the help of FE models, without the need for time-consuming and cost-intensive experiments. The usually iterative experimental procedure to find process parameters that enable a successful manufacturing process is replaced by a more efficient iterative optimization within an FE environment. In this way, the best possible parameter selection can be determined directly without material expenditure, in order to then manufacture the parts using the process combination. The optimization is mostly automated and virtual. As part of the further development of the tool, the remaining manual steps (such as the transfer of the results of the optimization between the process steps) are also to be supported by a software solution and the expansion and validation of the planning tool for other geometries is to be advanced.

20.3.3 Toward an Agile Development of Laser Process Simulations Using Port-Hamiltonian Systems

Models of laser manufacturing processes live in different physical domains. The laser beam is an electromagnetic wave and, therefore, obeys Maxwell's equations. The beam can heat up a material, which is described by the heat equation.

High-temperature gradients occur during processing yield distortions, which is studied in solid mechanics. Hence, the analysis of laser manufacturing processes is a multi-physical endeavor. In addition, even small changes in the process, such as the switch from a sheet metal body to a plastic body in a car, can cause significant changes in the physical phenomena of, e.g., laser welding, which needs to be accounted for in a simulation. Finally, the laser manufacturing industry has already matured, and the trend goes toward the analysis of whole processes, e.g., the additive manufacturing process, instead of individual phenomena like laser-material interaction (Dahotre et al. 2022). To develop digital shadows and design tools, which predict desired properties of a prototype and hence enable an agile product development, it is therefore essential to account for the relevant multi-physical regimes and processes as well as material data.

In recent years, port-based modeling techniques from electrical engineering have been combined with Hamiltonian mechanics and concepts from differential geometry to form port-Hamiltonian systems (pHs) (van der Schaft and Jeltsema 2014). One of the key ideas underlying this modeling language is the separate description of energy-storing, energy-dissipating, and energy-routing elements as well as the definition of an interconnection structure, called (Stokes-) Dirac structure, which preserves power. Within the pHs framework, different physical phenomena can be described and analyzed separately from another. There is an ongoing effort to apply structure-preserving model reduction techniques to pHs to solve distributed parameter systems keeping the properties of the pHs, i.e., the power conservation and composability (Argus et al. 2021). In addition, a visual modeling language called bond-graphs exists, which is used to describe and reason about the simulations at an abstract level (Borutzky 2011). The interconnection properties of pHs enable the simulation of complex processes systematically composing simulations of elementary processes. This systematic approach also allows modifying or adding sub-models, which enables short development iterations and continuous feedback. Therefore, pHs have the potential to enable an agile product development tool with which one can interchange sub-models to more easily answer change requests that might require different physical phenomena to be included in a simulation. In addition, the ability to bring problems in input-state-output form can be used to integrate process data in, e.g., a control loop or to integrate machine learning techniques. The input-state-output form also allows the integration of simulations in a data pipeline as it consumes a data stream as input and produces another one as output.

The separation of concerns inherent in pHs modeling has been used to model the different physical phenomena occurring in a coupled thermo-elasticity problem (Brugnoli et al. 2021; Argus et al. 2021) separately (c.f. Fig. 20.3 top left and top right).

Coupling the pHs of the heat conduction and linear elasticity problems yields again a pHs which can be represented as another bond graph (see Fig. 20.3 bottom center).

To show the potential of pHs in laser process simulations the authors are going to apply this modeling technique to predict thermally induced distortions occurring

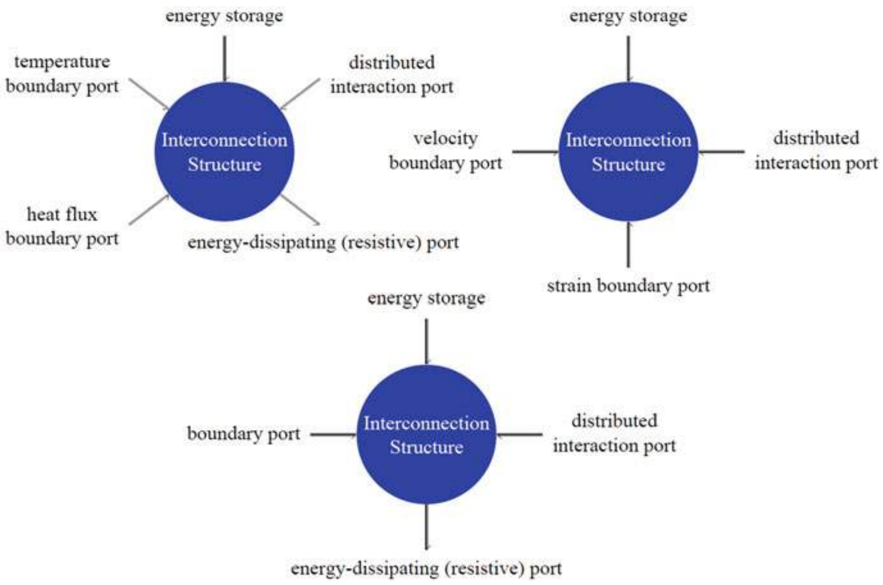

Fig. 20.3 The top left and top right bond graphs model a heat conduction, and a linear elastic structural mechanics problem, respectively. The combined bond graph is shown below

in laser additive manufacturing. The focus will be on the separate implementation of the sub-processes, and the interconnection of the reduced models at a later stage to form a co-simulation, which enables the use in design tools for additive manufacturing.

The pHs framework is a flexible approach to the mathematical modeling of multi-physical phenomena. It is used to study lumped and distributed parameter systems alike and, because of its interconnection properties, paves the way to develop co-simulations of complex systems or processes one step at a time.

20.3.4 Modularity for 4D Textiles

The production of textiles is one of the oldest production techniques for products often worn close to the body. Recent developments focus on the creation of near net shape fabrics that allow for individualization on the one hand and conserving resources on the other hand. The process of three-dimensional printing, creating 3D structures by adding layer by layer of material, goes along with these requirements. The process of 3D printing with plastics was further developed into four-dimensional (4D) printing. In 4D printing, material structures are produced that can change their properties over time in a targeted manner. The fourth dimension describes the time in which a change in properties might occur after 3D printing, introduced by the influence of an external stimulus. The energy for the change of property is stored in the material and/or is introduced by the stimulus (Tibbits 2017).

Building on the principle of 4D printing, 4D textiles are textiles that can change shape or function over time by the influence of a stimulus, mainly force and heat. The shape change properties can be introduced in all textile production steps, such as fiber and fabric production and finishing (Pei et al. 2015). 4D textiles produced by 3D printing on prestressed textile (usually warp or weft knitted with elastic material) shape change from a 2,5D structure to a 3D structure resulting in bistable structures and hybrid systems of a minimum of two materials. By prestressing the textile, energy is brought in by using both the structural and material-based elasticity of the fabric. The prestressed textile is brought in as the new build surface. By printing beams on the fabric, the reset can be programmed thus resulting in defined 3D shapes (Koch et al. 2021).

Mainly fused filament fabrication (FFF) with thermoplastic materials such as PLA, TPU, or ABS is usually used. Tessellation techniques are used to design the printing patterns (Koch et al. 2021). Only few approaches exist that model aspects of the behavior of 4D textiles. Kycia and Guiducci present an approach to model lines (Kycia and Guiducci 2020), Perèz et al. model Kirchhoffsche plateau principles to design complex interaction principles (Pérez et al. 2017). 4D textiles have proven to allow rapid prototyping of complex shapes and prototypes. As a design method, Schmelzeisen et al. proposed an adapted Design Thinking approach to integrate both the need-finding and the technical definition process in one (Schmelzeisen et al. 2018). The current process results in a variety of models and applications. Models rarely build on each other thus knowledge must be generated for every new model (Fig. 20.4).

To enable the development of MVPs, 4D textiles are defined as propagating structures, a concept derived from nature. These structures are open and entangled which enable them to be resilient and adaptable. Building on this, 4D textiles are digital materials that consist of a discrete set of parts (modules), which are reversibly joined (Popescu et al. 2006). Each module performs a function and is linked to other modules along the edge to build a system. An input at one point of the systems can turn the whole system into something completely different with a different function. For validation, three basic modules have been designed and the concept of propagation using user interaction with these modules and simple joints has been tested. The modules represent three core properties of the material:

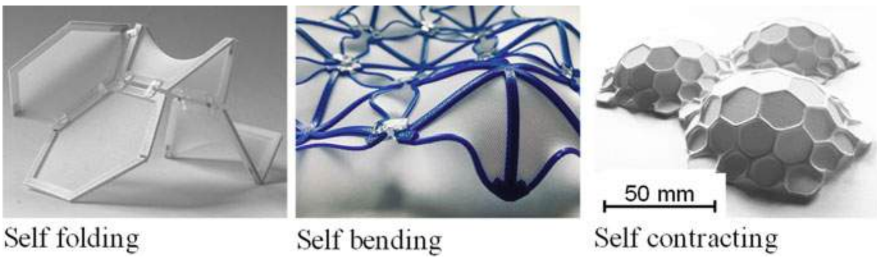

Fig. 20.4 Basic modules of 4D printing on textiles: Self-folding, self-bending, and self-contracting

Self-contracting, self-bending, and self-folding. The combination of modules with joints allows for complex structures. Modularity as design approach for MVPs thus for agile product development has a high potential for three reasons: the complexity to describe separated modules decreases, standardization of the modules helps to bring them as objects in the product design process (e.g., CAD) and scaling principles from micro to nano level. The modular design allows to build complex systems of basic modules for different application fields. Huge potential lies in architecture, medicine, interactive surfaces, and robotics.

20.3.5 Functionality for Free – Paving the Way for Multi-Material Additive Manufacturing

Fused filament fabrication (FFF)) is an established additive manufacturing (AM) process for prototyping of thermoplastic components. Its popularity is based on inexpensive equipment, high usability, and accessible process control (Osswald 2017). Many FFF processes are suitable to process two different colors or materials subsequently. A second material is mostly used for support structures, and interlayer adhesion between different materials is often weak. Due to its manner of adding material locally, one major advantage of AM is the ability to change material composition and density within a component. By intentionally varying applied materials and thereby integrating multiple functionalities in a single component, tremendous potential for agile prototyping is unlocked. This technology enables the evolution from a contour-dependent design approach to a material-centric, performance-driven design approach (Loh et al. 2018). Starting from the initial idea, the final product can be conceptualized by focusing on the material and its distribution rather than having manufacturing or design constraints shape the final morphology. Employing agile principles, this allows a rapid response to design and requirement changes as the material can be adapted in its composition and thus its function in a single-step process. Therefore, the time from idea to prototype and finally the product shortens significantly. Single components can substitute assemblies and users are able to reduce the dependency on suppliers for off-the-shelf equipment of small products. A low degree of adhesion between multiple materials in FFF, however, limits the range of possible applications and displayable functionality.

This research aims to understand and improve the process of multi-material FFF to support prototyping within the scope of agile product development. Smooth transitions between different materials can be generated by employing a nozzle design that combines two feedstock materials and deposits them in a single bead. Adhesion is expected to improve as opposed to distinct and subsequent material extrusion due to molecular processes that are initiated by pressure and temperature within the nozzle, as well as macroscopic mechanical interlocking within the prototype (Kennedy and Christ 2020; Khondoker et al. 2018). Moreover, compositional changes during printing allow for the creation of so-called functionally graded materials (FGM) whose properties can be tuned spatially. FGMs are known from nature where a graded structural transition allows for, e.g., optimized load transfer in bones or wood (Oxman 2011).

Identified use-cases for components by functionally graded multi-material additive manufacturing (FGAM) spread from e-mobility to an integrated Internet of Production. Within e-mobility, graded reinforcement can support the design and production of lightweight structural components. Within the Internet of Production, conductive gradients within components may support failure monitoring: By continuously measuring conductivity of abrasion-loaded manufacturing tools, existing machinery may be digitalized without the need for larger investments.

Experiments are conducted with a modified FFF desktop machine. The two materials are jointly molten and deposited by a single nozzle. The modification of common g-codes by a parser allows the continuous adjustment of the ratio of extruded material according to a previously determined gradient. During the built-up, process data is continuously measured. A hotspot allows the data transfer between printer and an exchangeable computer. Data records shall be analyzed to indicate both building progress and potential failure. General knowledge shall be extracted to be applicable for any subsequent and unique prototyping process.

Holistic experiments have been conducted for the combination of a brittle polylactide acid (PLA) and a ductile thermoplastic polyurethane (TPU) with the possibility of changing the composition in the process. Statistical analysis of the samples demonstrates a profound relationship between the content of TPU and properties like the elastic modulus, tensile strength, and correlated strain. Specimen's properties depend on design features like the composition ratio or the course of the gradient as well as on process parameters like temperature profiles.

Two main challenges remain within the process: First, material selection requires careful consideration, since the separation of jointly processed FGMs of dissimilar materials is difficult. A possible solution may be the combination of a compostable and a recyclable material. The combination of a virgin material with a secondary material might increase the usability of pre-used materials of lower quality but limits the integration of advanced functionality compared to the use of dissimilar materials. Second, the complexity for designers in FGAM increases drastically due to adding the dimension of material composition. An intuitive and predictive software to support users with the spatial assignment of macroscopic and microscopic material properties is required (Gebhardt et al. 2019). Only by ensuring predictability of part performance of a heterogeneous component with compositional material changes, FGAM will be suitable for advanced prototyping in different industries.

20.3.6 A Tool for Algorithmic Generation of Lattice Structures for Additive Manufacturing

Lattice structures are lightweight constructions which have specific characteristics, such as high surface area to volume ratio and excellent strength to weight ratio (Savio et al. 2018). Additive manufacturing (AM) technologies for the processing of metals, specifically laser powder bed fusion (LPBF), enable the fabrication of such complex structures. However, there exist challenges with the generation, data pre-processing, data handling, and simulation of AM-compliant lattice structures. The lattice structures created by most of the CAD software products are usually non-conformal, and they usually do not consider AM-specific producibility constraints such as minimum allowed distance between CAD features or threshold overhang angle which could result in failure of the AM fabrication of lattice structures. Furthermore, working with volumetric CAD data for the creation and pre-processing of lattices is usually difficult and non-real-time, and the generation process may fail when working on CAD data generated by another software. Moreover, the simulation of lattice structures is challenging due to a large number of mesh elements (Dong et al. 2017).

To address these issues, an algorithmic approach for the generation of lattice structures is introduced in which the AM producibility constraints are respected. This requires creation of a database including producibility data for each AM production machine and material. Furthermore, algorithms for the generation of AM-compliant conformal lattices are developed; the stiffness and strength of conformal lattice structures could be higher than trimmed lattices (Liang et al. 2018). To analyze and improve the behavior of lattice structures under mechanical loading, they are simulated and optimized. The simulation approaches aiming at the reduction of mesh elements while predicting the behavior with high accuracy are also developed and linked to the lattice generation tool, as depicted in Fig. 20.5.

The developed tool can automatically create lattice structures which conform to AM production constraints and then locally adapt the meshing techniques to ensure finer meshes at strut joints. Cubic/cuboid use cases with an f_2cc, z unit cell of a size of $3 \times 3 \times 3$ mm^3 were meshed adaptively and simulated under mechanical loading

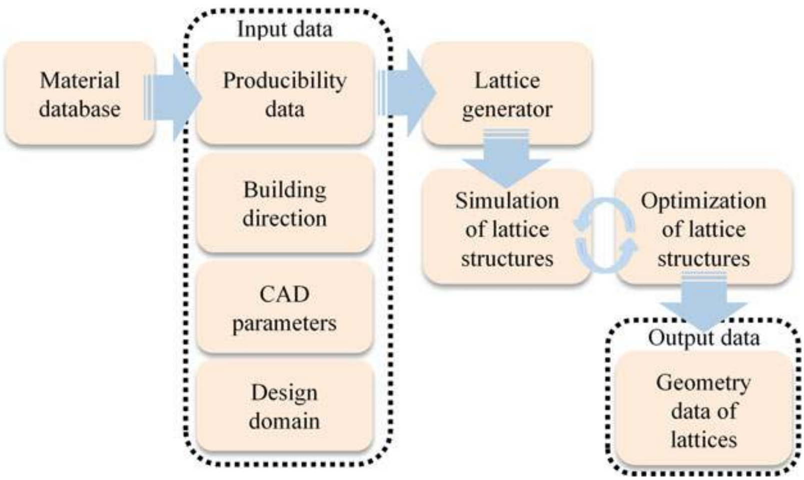

Fig. 20.5 The framework for the algorithmic generation and optimization of lattice structures

in the elastic regime, and they produced comparable results with that of uniform meshing with a difference below 1% while reducing the number of elements per unit cell by approx. 70%.

The developed tool should be further equipped with algorithms for the creation of lattice structures for arbitrary freeform design spaces. In addition, the simulation approaches should be further enhanced for lattice structures with a larger number of mesh elements. For the optimization of lattice structures, refinement algorithms and/or size optimization methods should be implemented. The created tool enables agile product development of lightweight efficient structures by quick adaptation of the design in response to the requirements of the material, load and boundary conditions, and customer demands such as the topology and geometry of lattice structures. Furthermore, the tool handles the data in a smart manner by generation, simulation, and optimization of the structures in one platform to eliminate or remarkably reduce the involved challenges with lattice processing. The created lattice structures could be used in biomedical, heat transfer, hydrogen storage and vibration control applications (Du Plessis et al. 2022) as well as in heterogeneous catalysis. The data acquired from simulations can be stored as a part of the digital twin of lattices and can be used for optimization purposes.

20.3.7 Agile Alloy Development for Metal Additive Manufacturing

During the last years, the field of additive manufacturing (AM) of metals has witnessed the rise of data-driven approaches as an enabler for agile product development. Numerous examples of data-driven approaches can be found in component design (Oh et al. 2019), in quality control (Tian et al. 2021), and defect detection (Scime and Beuth 2018). So far, the development of new alloys for metal AM depends on time-consuming experiments and simulations to understand process-microstructure-property (PSP) linkages and requires high computational costs. We propose a framework (Fig. 20.6) that provides python-based tools for an efficient description of linkages between additive manufacturing process, microstructure, and mechanical response of metals for AM. The framework contains different strategies to differentiate cases of different complexity level (e.g., low-complexity morphology-dominated and high-complexity morphology- and texture-dominated microstructures).

The results in Fig. 20.7 present an example for building a relationship between process parameters based on physics-based kinetics Monte Carlo (kMC) simulations and the corresponding microstructural feature in terms of the directional chord length distribution (CLD). Directional CLDs capture the morphological characteristics in 3D of AM microstructures. Further data compression by principal component analysis (PCA) reduces the data space for building efficient relationships by ML-based regression algorithms. Regression models substitute computational expensive kMC simulations for new queries on the process parameters of interest. The framework will be extended by an invertible neural network to get direct predictions on the design space (e.g., chemical composition, laser speed, etc.), since typically

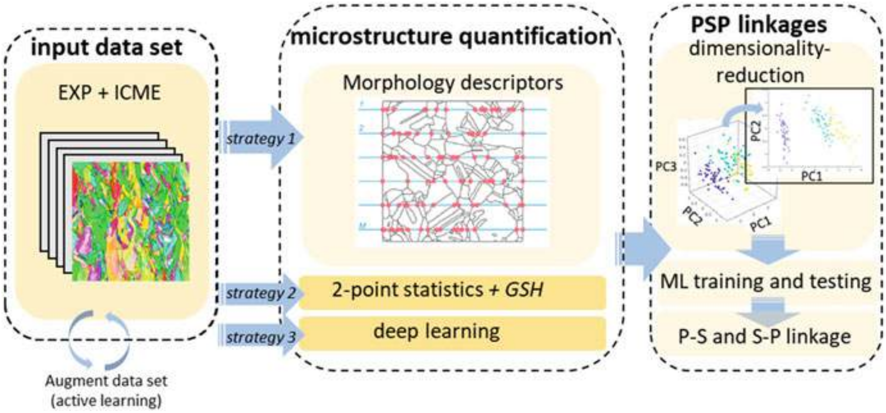

Fig. 20.6 Data-driven/ML framework to establish Process-(micro)Structure (P-S) and (micro)Structure-Property (S-P) linkages (forward-propagation) as the basis to find inverse solutions for an optimized AM design space

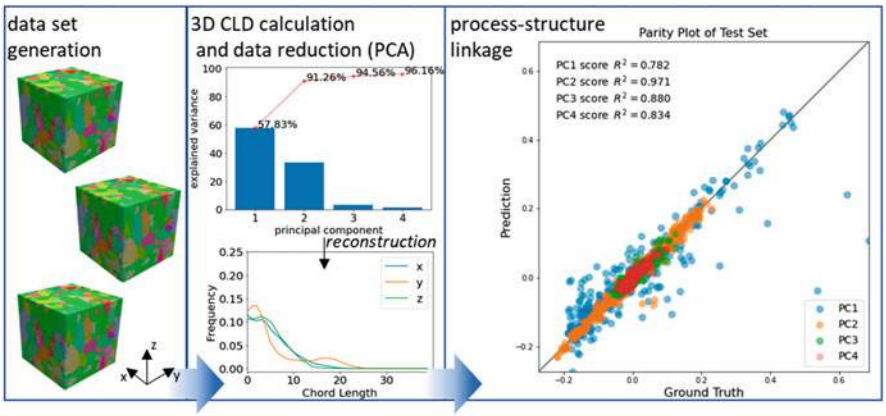

Fig. 20.7 Revealing the P-S linkage during AM derived from 3D microstructures using a data-driven framework. Applied 3D chord length distributions (in x-y-z directions) of the microstructures reduced by PCA represent input data for the model. The P-S relationships are predicted by ML-based regression as output. In total 960 represented volume elements (RVE) simulated with a SPPARKS kMC subroutine (modified Potts-Monte Carlo model (Rodgers et al. 2017)) account for the used input data

the development of new alloys requires answers to inverse-directed questions (e.g., what is the process parameter space to reach a certain deformability?). In summary, the framework enables fast and computational efficient predictions along the P-S-P chain.

20.3.8 Optical Systems Development

For various applications in laser material processing, such as laser welding, polishing, or engraving, individual optical systems are required depending on the laser source and desired beam characteristics. The optics design is a time-consuming process and depending on the complexity of the system experts need up to several weeks or months for designing, analyzing, and tolerancing. For many custom designs the employed lenses must be individually manufactured, which is expensive. This can be circumvented by adaption of the optics design for the use of low-cost stock lenses. For agile product development, the time and cost factor for an individual lens manufacturing is not sustainable.

To make the design of optical systems accessible for agile product development, an application is developed which automatically designs optical systems from stock components, which are available quickly and at low costs. These optical systems are used for the first prototype application and are continuously improved during the agile development circle. In the first prototyping step, as a demonstrator a three-lens system is considered.

The design of a three-lens system is realized by computing all possible combinations of commercially available stock lenses from a given catalog (König 2021; König et al. 2021). In order to avoid a calculation time that increases cubically with the number of stock lenses and to minimize the amount of time-consuming exact ray-tracing calculations, clustering methods of the configuration space as well as simplifications of the optical propagation (the so-called paraxial raytracing) are used. A subsequent automated tolerance analysis (König et al. 2017) against assembly deviations allows the design of robust optical systems such as the plane-field optics shown in Fig. 20.8.

For agile product development, continuous adjustments of the optical design are necessary to meet the changing requirements of the stakeholders. The three-lens

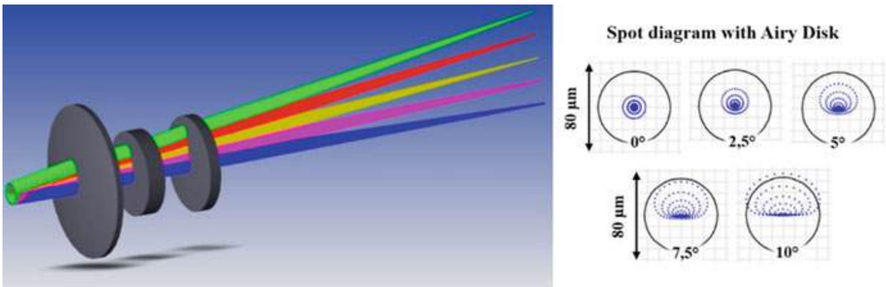

Fig. 20.8 Exemplary design – Plane-field optics with 6 mm laser beam diameter, 150 mm focal length, 10° field angle, and 1064 nm wavelength. The system is smaller than 50 mm in the length. The incident rays on the image plane are within the airy disk, which describes the maximal physical focusability for an optical system

system must therefore be adapted, improved, and finalized to the new requirements. This usually results in optical systems with a large number of lenses.

To carry out these adaptations, the next step is the development of a method based on artificial intelligence (AI) for automated optics design (Fu et al. 2021, 2022). Utilizing reinforcement learning an agent has to be trained to set up and optimize an optical system. The agent automatically adapts an existing prototype (start system) to find a design matching the new requirements of the stakeholders. This can be done within few minutes to reduce the latency time in the agile product development.

20.4 Conclusion

In this chapter, the development of enabling technologies and interactive tools for an agile product development in the context of the Internet of Production (IoP) is presented. For this purpose, the state of the art of agile product development is described as an introduction. Building on this, advanced manufacturing technologies (AMTs) are presented as enablers and tools in the context of agile product development. Here, the possible uses of AMTs as manufacturing processes for prototypes are further developed. For each AMT, usage and integration of the technology and data acquired during manufacturing in agile development environments is explored. Also, the use of relevant data from production and material to determine the minimum viability of a product prototype as well as to select, adapt, and improve the respective prototyping technologies is investigated.

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Part VII

Integrated Usage

Interplay Between Company-Internal and -External Perspectives on the Internet of Production: Implications for Governance, Organization, Capabilities, and Interfaces

21

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Abstract

The Internet of Production (IoP), the global and integrated use of production data, will completely reshape how organizations operate and interact with each other. We introduce how these developments will affect the usage phase including value creation and capture in the future manufacturing ecosystem. Our analysis highlights requirements and implications for governance, organization, capabilities, and interfaces. These factors are considered from both a company internal and a company external perspective on usage as well as in terms of their interplay. The internal perspective focuses on the role of humans in interacting with IoP-based technology in future socio-technical production systems. The external perspective describes how value is captured and shared between stakeholders by incorporating data based on platform-based industrial ecosystems. The interplay of the two perspectives is exemplarily discussed using a foresight study on next-generation manufacturing.

21.1 Integrated Usage

The Internet of Production increases the opportunities for gathering data in the development, production, and the usage cycle of companies. Within the user cycle, data about the usage of products is collected and shared between other domains to enable the development of products, processes, and even business models. However, usage data are seldom utilized across companies or departments to optimize operations, investment decisions, or innovation processes. Learning and analytics can take place faster and more efficiently if manufacturers not only utilize their own data but also can access data from similar contexts in other entities. Our work describes the interplay and trade-offs between governance, organization, capabilities, and interfaces (GOCI) from a company-internal and -external perspective to enhance sustainability and profitability in an Internet of Production (IoP, see ► Chap. 1, "The Internet of Production: Interdisciplinary Visions and Concepts for the Production of Tomorrow"). The vision is to foster IoP-based value creation during the usage of connected data, products, and equipment by the selection of a governance mode, a specific organizational structure, development of capabilities, and the design of interfaces. Both an internal perspective and an external perspective resulting from the connectivity and networking of data, assets, and users forming a business ecosystem are needed to realize this vision.

From an internal perspective, context-aware and user-adaptive interfaces between humans and machines are the enablers for realizing the operational benefits of the IoP. Task demands must correspond to human operators' physical and cognitive ergonomic requirements to support efficient task execution and responsible decision-making. The external perspective covers the availability of data and capacity of third parties and how the resulting value is captured and shared among the actors. A third focus is on the interplay between the internal and the external

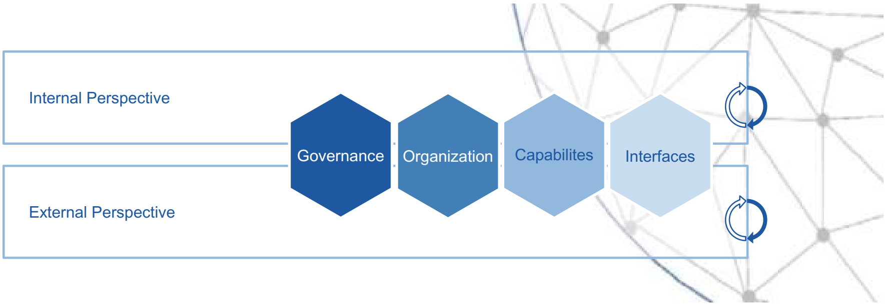

Fig. 21.1 The GOCI-Framework

perspective and the tradeoffs and frictions that evolve from different principles of sustainable value creation from both perspectives. For the realization of this vision, our research builds on the work of Gawer (2014) and Parker and van Alstyne (2018). The structure is guided by a set of four factors that govern the implementation of the IoP internally and externally: governance, organization, capabilities, and interfaces (see Fig. 21.1).

The four factors are discussed in detail for the internal and external perspective as well as the interplay between the two.

21.2 Internal Perspective: Acceptance and Sustainability of the IoP Application Within a Socio-Technical System Approach

21.2.1 Research Direction and Issues

Irrespective of their role and background, humans will continue to be an essential part of the complex socio-technical system into which the IoP is embedded. However, their tasks, required qualifications, and work structures will change, as will the tools they use, how they exert influence in the overall work system, and the allocation of responsibility for decisions.

Novel forms of hybrid teamwork in production context, e.g., human-robot collaboration, AI-based support for decision-making processes, and an appropriate mapping of human skills and capabilities to the technical systems form the basis for an efficient, target-group specific interaction in cyber-physical systems. The integration of more and more technical support systems and progressive process automation, particularly in the area of production systems, will constantly increase the proportion of knowledge-intensive work, while the proportion of physically demanding work that must be performed by humans will constantly decrease. As a result, the focus, which has traditionally tended to be on the physical strain of employees, must shift to take cognitive strain into account to ensure sustainable working conditions. To this end, the approach already established in the production process of using digital shadows to analyze and prospect for future developments must be explicitly expanded to include relevant data from human actors. This will allow for enabling the socially sustainable design of the entire work system in all four GOCI dimensions, taking into account appropriate data protection, privacy, and personal self-determination in the form of a human digital shadow (Mertens et al. 2021). Finally, possibilities to establish operational and organizational structures to support collective production intelligence have to be identified to enable holistic knowledge building and management. The goals of the internal perspective are, therefore:

1. Create ergonomic, transparent, trustful, and responsible interfaces and decision support systems for production systems and the IoP.
2. Automate human knowledge and expertise for the human-centered design of hybrid teamwork and for the exchange of best practices.
3. Ensure professional profiles and qualifications of the working person to allow efficient, effective, and satisfactory interaction between all entities of socio-technical production system.
4. Support in work process design and strategy development to promote socially sustainable solutions and to take into account ethical, legal and social implications as an immanent part of change management.

21.2.2 Preliminary Work and Background

Earlier research has already considered human-centered design aspects for creating a socio-technical framework for the Internet of Things (Shin 2014). Taking the example of human-robot collaboration, previous work mainly focused on safe collaboration and technological solutions in order to avoid safety guards (Wang et al. 2017). In contrast, ethical and moral aspects have been investigated in social robotics or medical applications. For mastering the increasing complexity and information available in the IoP, decision support systems must be adapted to the requirements of human operators and their diverse needs (Keim et al. 2010). Despite the vast amount of research on visual, cognitive complexity, and interface design methodology, these findings are often neither transferable for the context of production, nor do they provide actionable guidelines for designing sustainable interfaces for socio-technical production systems.

Prior work in the context of previous funding phases has covered the iterative and user-centered design, development, and evaluation of support systems for working persons. Here, an empirical modeling of users' needs considered factors like user diversity, acceptance, and compliance with interactive systems. Human-centered interaction design was applied, for instance, in contexts of intelligent decision support assistance systems for production planning and control, supporting the operator as a decision maker with appropriate information acquisition, data aggregation, and operation choice (Nelles et al. 2016). Further studies on information complexity (Ziefle et al. 2015) and the relations between trust, technology acceptance, human efficiency, and effectivity (Brauner et al. 2017) stressed the importance of a user-centered approach (Stiller et al. 2014). To enhance the conformity of semiautonomous robotic assembly processes with operator's expectations, cognitive automation was applied by simulating human assembly and decision-making strategies (Faber et al. 2017). While higher degrees of automation and occupational safety have already been addressed, important ergonomic and moral questions are still open.

21.2.3 GOCI Dimensions

The internal perspective on usage in the socio-technical workings system IoP is mainly shaped by the involvement of the human in the underlying production processes. An economically and socially sustainable implementation of the IoP requires appropriate operational and organizational structures to enhance communication and knowledge transfer between working persons, digitalized production technology, and customers as well as the readiness to adapt to changing conditions in the sense of continuous human-oriented change management (see Fig. 21.2).

Governance. The IoP changes organizational processes, structures, and management strategies, yielding new requirements for the internal governance of these

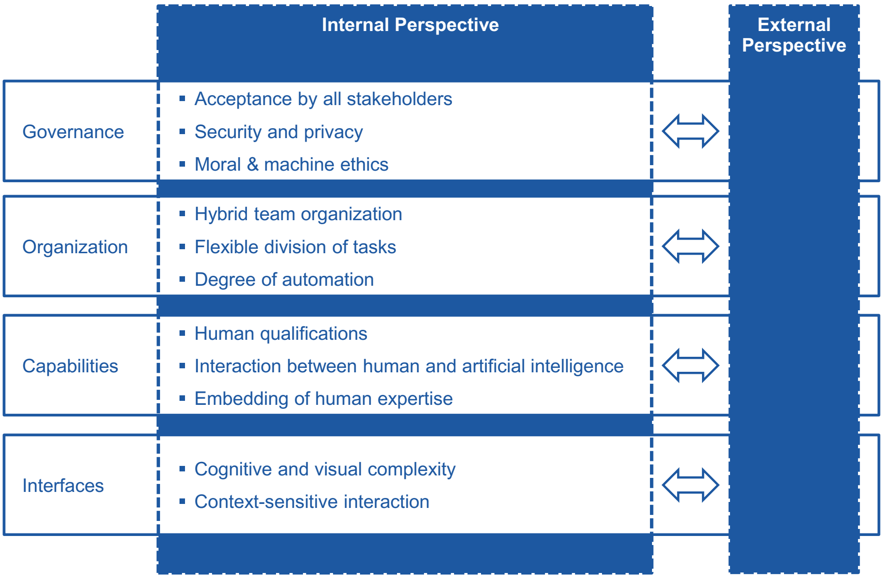

Fig. 21.2 Main aspects of the internal perspective on the usage phase in the IoP (structured according to GOCI scheme)

systems. To ensure broad acceptance, the diverse stakeholder perspectives must be continuously taken into account to allow holistic decisions. The ethical, legal, and social implications should be an intrinsic part of this decision-making process. To enable this in such a dynamic environment, there is also a need for appropriate methods that guide the people involved and consider the entire utilization phase. At the same time, decision-making by autonomous, human-like systems must ensure transparent processes, security, and privacy.

Organization. A sustainable socio-technical production system is characterized by a highly flexible organizational structure and hybrid team organization, which enables reacting to changing conditions in a short-cycle manner. The example of human-robot collaboration stresses that inter-team communication as well as ergonomics in the workflow are crucial for safe and effective collaboration. Hybrid team organization has to ensure acceptance by the working persons, flexible division of tasks, and mutual learning and adaption processes. Despite the elimination of mindless decisions, strategic decisions still depend on humans who have to perceive and process increasingly complex multi-dimensional data sets and to make decisions whose effects are increasingly difficult to forecast. In particular, this demands an organizational setup facilitating higher work productivity, the acceptance and willingness of the human actors to adopt and use novel technology, the ergonomic design of working and learning environments, and the promotion of mutual learning.

Capabilities. With raising amounts of available data, persons involved into production need to manage multiple production processes or collaborate with multiple robots simultaneously. Advanced decision support systems can reduce the cognitive load by analyzing, e.g., best practice examples with regard to the relevant success factors. Necessary qualifications will be deviated and concepts to enhance trust into this artificial intelligence investigated within the context of holistic change management to develop the future of production work in a participatory way. Aiming at intelligent support and control systems, ways of representing human experience and competence in solving indecisive and unstructured problems are of particular importance for a sustainable solution.

Interfaces. An increasing digitalization and connectivity of devices implies challenges by raising the amount of production data available, causing high cognitive and visual complexity to handle these data and associated cognitive strain. Although the data of cyber-physical production systems are generally preprocessed by the infrastructure to be understandable for people at all, there are multiple application scenarios which require context-specific data visualization. Especially with an increasing complexity of the operator's task, appropriate decision support systems following context-sensitive design principles are required. In case of human-robot collaboration, for instance, both the interface for data visualization and the physical interaction design are of crucial importance.

The aforementioned challenges require placing the human directly into the loop of the development and production process, providing knowledge about human factor requirements in digitalized production environments.

21.3 External Perspective: Designing Mechanisms for Value Capture in Business Ecosystems for the IoP

21.3.1 Research Direction and Issues

The IoP is, by definition, not restricted to a focal company or value creation within a closed network of established partners. Instead, it resembles the vision of an open network of sensors, assets, products, and actors that continuously generate data. A core element hence is the (re-)use of data, digital shadows, and applications by other parties to facilitate faster and more efficient learning and analytics. Therefore, incentives, governance as well as new ways of user integration are necessary elements to make this vision a reality. The rise of platforms (business ecosystems) where these data is being exchanged and enhanced by dedicated "apps," often offered by specialized third-party entities, is one of the largest current economic trends (Rietveld and Schilling 2021). To create value, ecosystems rely on complementary inputs made by loosely interconnected, yet independent stakeholders (Parker and van Alstyne 2018). In the case of the IoP, platform participants include the orchestrator of the platform, operators of production assets (users in form of factories), and providers of applications analyzing data and providing decision support (app programmers). In addition, the goods being produced can also become part of the platform in form of connected ("smart") products. With this, end-users (customers) also become a participant. Among these participants, dedicated mechanisms governing data access and privacy are required. At the same time, the ability to implement the vision of the IoP is a question of setting the right incentives to align the different interests and priorities of the partners involved. Objectives of the external perspective are therefore:

1. Establish the IoP as an open ecosystem for industrial data of both machines (assets) and products produced in the usage stage
2. Managing the tension between openness and control in order to allow for value capture of all actors involved
3. Provide a set of managerial decision parameters when setting up an industry platform around the IoP

21.3.2 Preliminary Work and Background

Open platforms offer distinct economic advantages. They allow a firm to harness external inputs and innovation as a complement to internal innovation by facilitating an exchange between users who otherwise could not transact with each other (Parker and van Alstyne 2018). Theoretically, platforms (also: two-sided markets) have been investigated in the industrial organization literature. Essential to most economic definitions are the existence of "network effects" that arise between the participants (Gawer 2014; Allen et al. 2021). Platforms typically reside upon a layered digital infrastructure, where lower-level layers (e.g., physical components) enable and support functionalities at higher, user-facing layers. A recent stream of literature complements the economic analysis by studying distinct governance and orchestration challenges. Less work has addressed the situation of the IoP that depends on the concurrent commitment of complementary inputs from independent stakeholders towards a de novo ecosystem creation effort (Dattée et al. 2018). A core decision here is platform openness (e.g., Ondrus et al. 2015; Parker and van Alstyne, 2018). Dattée (2018) provides an analytical model for this situation, and Benlian et al. (2015) investigates complementors' decision to join a platform based on its openness.

Jiang et al. (2017) investigated market structure effects and the rise of manufacturing platforms for Additive Manufacturing, highlighting the demand for appropriate governance mechanisms (IP protection, user integration, etc.). Platforms also represent a key concept in research on business models for Industry 4.0, where methodologies were developed to model BM alternatives (Adner and Rahul 2010; Kapoor and Nathan 2015; Wang and Miller 2019). The Fraunhofer Industrial Data Space initiative (Otto et al. 2017; Jarke 2017) has focused on requirements and rather technological challenges of inter-organizational data exchange. This requires novel conceptual information modeling and significant research for applications in production engineering. In conclusion, previous research has investigated the application layer, i.e., defining elements for value creation out of the digital shadow. Basic mechanisms of platform markets are well understood, too. However, dedicated research in the context of industrial data applications is missing, as well as on work on value capture, i.e., models to appropriate economic rents from the IoP. Platform openness has been derived as a key variable in this context. The larger the openness, the higher the likelihood of value creation (in terms of generating novel insights from data), but the lower the ability to capture value by one actor. Large openness also supports free-riding, i.e., participating at the fruits of data sharing while not contributing to the data stock.

21.3.3 GOCI Dimensions

Also, for the external perspective the four layers from the GOCI framework guide the research on value creation and capture through the integration of data based on data- and platform-based industrial ecosystems. (Gawer 2014) – see Fig. 21.3.

Governance. The central construct here is the degree of openness vs. desire for control of each actor in the ecosystem. This delicate tension balances the level of value creation for all ecosystem participants and the level of value capture for each participant, i.e., how actors can contribute to and profit from the ecosystem. Governance also determines the rules for data exchange across organizations. Possible governance modes (and patterns of platform governance) need to be identified and matched to the performance of observed use cases.

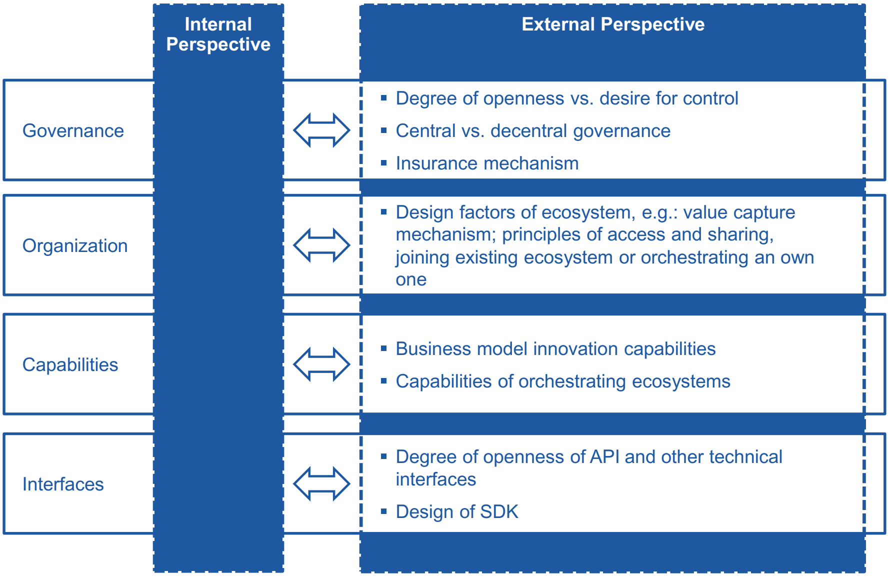

Fig. 21.3 Main aspects of the external perspective on the usage phase in the IoP (structured according to GOCI scheme)

Organization. Organizational forms refer to the design patterns of a platform business model that structure value creation and capture. This also asks the question whether firms shall join an existing ecosystem (under which conditions) or try to orchestrate their own. The main question platform players need to ask is how they want to play and use an ecosystem. Further, organizational design deals with new forms of collaboration across organization and how to organize this within a focal organization.

Capabilities. Operating on an IoP platform demand new capabilities in firms, including business model innovation, mastering organizational change, or building an ecosystem. Actors in the ecosystem should all have the skills to contribute to the overall value creation. It is important to ask which capabilities are currently available and which need to be built up or provided by others. Platform-based ecosystems manage complementary capabilities to provide value that a single organization would not have access to. Further transparency can be generated across organizations which can lead to a more sustainable ecosystem. This leads to a re-interpretation of the central economic question of the boundaries of a firm.

Interfaces. With interfaces, a distinction must be made between interfaces on the platform and interfaces between platforms. From a platform perspective, the openness of an API is a signal of willingness to share data and knowledge, hence attracting third parties. At the same time, open interfaces can be a technical risk and reduce the ability to capture value. The central question for the platform orchestrator is how to achieve a competitive advantage through strategic openness. Interfaces need to be designed to enable these exchanges and access while maintaining privacy and security. Open machine-to-machine interfaces are thus being investigated as a key design factor for the Internet of Production.

21.4 Interplay Between Internal and External Perspective: A Delphi Study

The elaborated GOCI framework does not only provide a structure in which individual research efforts from the internal and external perspective of usage can be integrated, but it also highlights opportunities for interdisciplinary research that combines the two perspectives and spans across the four dimensions. Thereby, the interplay between the internal and external perspective can be investigated identifying areas where tensions between the corresponding visions and future developments might arise. As an example, the approach and results of a Delphi study on usage-centered developments in the manufacturing industry in the upcoming decade are presented. A full presentation of the obtained results and a detailed discussion of their implications have been published by Piller et al. (2022).

Forecasting the future implications of IoP technology and processes on the manufacturing industry is made difficult by the high uncertainty of the technological advancements. Here, the Delphi method provides a structured approach to derive reliable future scenarios based on expert assessments (Landeta 2006). In an anonymous and multi-stage format, the experts rate the likelihood and future impact of a set of projections, aiming for a consensus in their assessments. By ensuring a high degree of diversity in the selection of both projections and experts, the method enables the inclusion of the perspectives of different stakeholder groups (Linstone 1981).

For the IoP Delphi study on the next generation of manufacturing, projections were developed for the four dimensions of the GOCI framework and a fifth, added dimension of resilience (Van Dyck et al. 2022a). The projection development process included workshops with a first group of experts from different scientific fields as well as a complementary literature review. After systematic refinement and pre-testing, 24 projections were selected for the expert survey (see Fig. 21.4). Then, an international panel of experts from both industry and academia assessed the projections in a real-time Delphi format (Gnatzy et al. 2011). The obtained quantitative and qualitative responses formed the basis for developing future scenarios for the manufacturing industry (Van Dyck et al. 2022a).

Overall, the experts agreed that the emergence of IoP concepts such as digital twins and digital shadows will shape the future manufacturing ecosystem (Pütz et al. 2022). Nevertheless, the expert assessments also highlight a high level of uncertainty about how exactly this digital transformation will look like. This observation emphasizes the need and opportunities for future research in this area. In the following, some of the key findings for each dimension of the GOCI framework are presented (Van Dyck et al. 2022b):

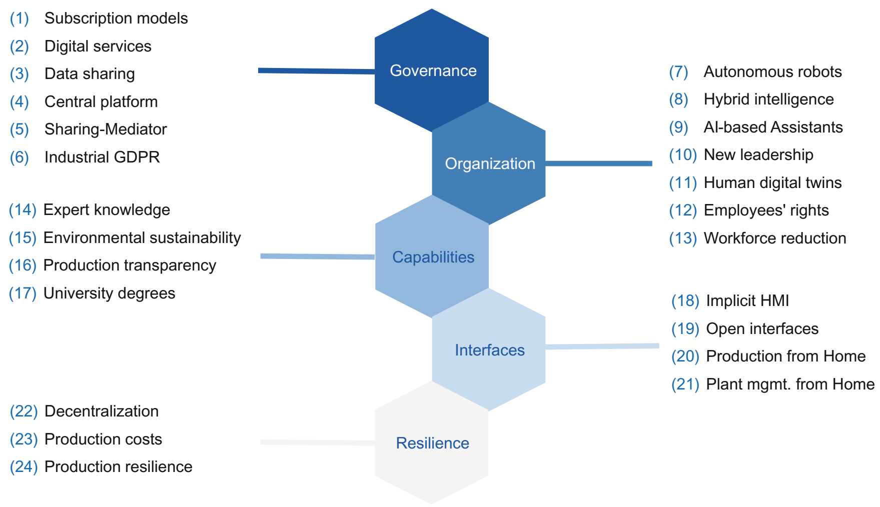

Fig. 21.4 The 24 projections investigated in the Delphi study on usage-centered developments in the manufacturing industry in the upcoming decade

Governance. Introducing open data sharing into the manufacturing industry is expected to create new opportunities for the cooperation of business partners within the manufacturing ecosystem and facilitate the emergence of corresponding business models. Based on this forecast, the experts also predict that digital services for production machinery will offer decisive competitive advantages as the margin for improving physical efficiency diminishes. Simultaneously, adequate measures for data protection and data security were identified as central internal prerequisites for the acceptance of these forms of collaboration. Consequently, industrial data protection regulations may be necessary to manage the tensions between internal requirements and external opportunities.

Organization. Experts project that the advancement of AI technology will have a significant impact on decision-making processes in the manufacturing industry, both on the shop floor and in production management. On the shop floor, the high level of standardization and large number of repetitions of individual work steps provide the optimal data basis for supporting production workers via AI-based assistance systems. In production management, managers will use similar assistance systems for short-term decision-making, improving multi-criteria optimization. However, experts also expect that when these forms of hybrid intelligence are used, humans will retain the responsibility and final decision-making, emphasizing the need for a highly skilled workforce.

Capabilities. The experts' assessments highlighted improving the environmental sustainability in the manufacturing industry as a major opportunity enabled by IoP capabilities. Similar to offering digital services for production machinery, providing solutions for making products and processes more environmental sustainable is expected to bring competitive advantages, as the corresponding demand from both customers and employees rises. In addition, the introduction of digital shadows and the associated increase in the transparency of production processes can facilitate production planning and forecasting, which benefits resource efficiency. Thus, the internal use of production data and the external demands imposed on the company can work hand in hand to push companies toward environmentally sustainable manufacturing.

Interfaces. The global use of production data in the form of digital twins and digital shadows will require the development of new interfaces both within and between companies. From the external perspective, the experts project a demand for regulatory requirements ensuring open and standardized data interfaces between organizations. However, they are doubtful that such standards can be reached in the next 10 years. From the internal perspective, the ongoing automation of production processes, shifting the focus more from repetitive manual work to cognitive tasks like automation supervision and decision-making, creates the need for new human-machine interfaces. Again, the experts doubt, however, that it will be possible to develop reliable implicit interfaces in the next decade, placing the focus instead on assistance systems such as cobots and AI-based decision support systems.

To conclude, the IoP Delphi study on future usage-centered developments in the manufacturing industry is an example for the methodical implementation of the elaborated GOCI framework. Specifically, the study demonstrated the feasibility of including research questions from all four dimensions of the framework into a joint research approach. Moreover, the analysis combined the internal and external perspective on usage, enabling the investigation of their interplay. The study, thereby, offered a holistic perspective on the usage dimension in the future manufacturing ecosystem.

21.5 Further Research

Current research results and a holistic view on the internal role of human actors within the socio-technical system of the IoP can be found in the ▶ Chap. 22, "Human-Centered Work Design for the Internet of Production." Specifically, measures across different levels of human-centered work design are presented to highlight the range of design dimensions that must be considered when aiming for a human-centered transformation of production work systems. For the work task level, guidelines for enabling efficient collaboration and cooperation of humans, robots, and smart agents in digitalized production systems are presented. A new framework for the classification of human-robot collaboration workplaces is introduced for the working condition level, and approaches for using corporate data to facilitate the knowledge transfer in global production networks and the implications of the IoP for new leadership models are discussed for the organizational level. Finally, the supra-organizational level is addressed in form of ethical considerations of how the IoP affects the understanding of responsibility and normative values in the work context.

An extensive literature overview of platform-based ecosystems and a holistic process model for platform-based ecosystems which builds on the four GOCI factors and the external perspective can be found in the ▶ Chap. 23, "Design Elements of a Platform-Based Ecosystem for Industry Applications." The process model bundles most relevant findings of 130 papers and classifies them into 4 phases and 16 design elements for a process-oriented approach. Further, four industrial use cases for specific phases and design elements are shown for an exemplary application in an Industry 4.0 context. It highlights the importance of specific data and outlines what data can be shared from an external perspective. Further, the research deals with the strategic modeling of platform-based ecosystems and the research addresses control points that platform actors can proactively establish in order to adapt their business models and to jointly create and capture value. Both researchers and practitioners benefit from a holistic framework for platform-based ecosystems and from concrete examples that provide insight into this emerging research area.

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Human-Centered Work Design for the Internet of Production

22

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Abstract

Like all preceding transformations of the manufacturing industry, the large-scale usage of production data will reshape the role of humans within the sociotechnical production ecosystem. To ensure that this transformation creates work systems in which employees are empowered, productive, healthy, and motivated, the transformation must be guided by principles of and research on human-centered work design. Specifically, measures must be taken at all levels of work design, ranging from (1) the work tasks to (2) the working conditions to (3) the organizational level and (4) the supra-organizational level. We present selected research across all four levels that showcase the opportunities and requirements that surface when striving for human-centered work design for the Internet of Production (IoP). (1) On the work task level, we illustrate the user-centered design of human-robot collaboration (HRC) and process planning in the composite industry as well as user-centered design factors for cognitive assistance systems. (2) On the working conditions level, we present a newly developed framework for the classification of HRC workplaces. (3) Moving to the organizational level, we show how corporate data can be used to facilitate best practice sharing in production networks, and we discuss the implications of the IoP for new leadership models. Finally, (4) on the supra-organizational level, we examine overarching ethical dimensions, investigating, e.g., how the new work contexts affect our understanding of responsibility and normative values such as autonomy and privacy. Overall, these interdisciplinary research perspectives highlight the importance and necessary scope of considering the human factor in the IoP.

22.1 Introduction

The goal in developing an Internet of Production (IoP) is to realize distributed networks of cyber-physical production systems (CPPS) by integrating digital manufacturing technologies and the large-scale collection and analysis of corresponding production data. Using this infrastructure, CPPS can effectively connect sensors

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capturing information about the physical environment and actuators interacting with it, linking the physical and digital worlds (Lee and Seshia 2016). While CPPS will enable further automation of production processes even in dynamic and complex task environments, their introduction is not expected to eliminate the need for human presence in production systems (Neumann et al. 2021). Instead, future production systems will be characterized by the close collaboration between humans and machines, thereby benefiting from the respective strength of both sides (Becker and Stern 2016). This observation highlights that the introduction of the IoP will not only transform the technical side of socio-technical production systems but will also reshape the role of the humans within them (Kaasinen et al. 2020; Rauch et al. 2020; Neumann et al. 2021). Most importantly, humans' tasks will continue to move away from repetitive manual tasks (Kadir et al. 2019) and towards cognitive tasks such as strategic decision making in production planning and control as well as problem solving (Fantini et al. 2016; Kaasinen et al. 2020). This shift in tasks will also change the skills and competencies required of workers, with an emphasis on information technology skills, self-organization, problem-solving, and communication skills for collaboration in interdisciplinary teams (Hecklau et al. 2016).

As the role of humans within production systems changes, it is important to consider how these changes affect both the humans' work performance as well as their physical and mental well-being (Dul and Neumann 2009). On the one hand, introducing CPPS provides unique opportunities for improving human work. Rather than replacing humans with technology, the transformation can be used to extend human capabilities so that their contributions become more effective and efficient (Gorecky et al. 2014). Central opportunities for this involve the flexible adaptation of the work system to the individual worker and the use of advanced assistance systems. Regarding work system adaptation, the analysis of production data can enable the adaptation of machine behavior, user interfaces, and production planning to the physical attributes, skills, experience, preferences, and current state of the human users (Villani et al. 2017; Kaasinen et al. 2020; Mertens et al. 2021). In addition, advanced assistance systems can support humans in dealing with a wider range of task responsibilities (Gorecky et al. 2014). Whereas cobots as a form of physical assistance system have the potential to reduce physical workload to a minimum, aid systems such as decision support systems can improve human task performance in cognitive tasks by providing the user with task-specific information and suggesting alternative actions (Rauch et al. 2020). Based on the aforementioned opportunities, researchers have envisioned the human worker in future production systems as a close collaborator of technical systems, using digital skills in innovative work processes that provide greater work autonomy and opportunities for self-development (Romero et al. 2016a, b; Kaasinen et al. 2020; Taylor et al. 2020).

On the other hand, the upcoming transformation of the production industry is also associated with threats for human job quality and job security. Foremost, while the described opportunities may benefit the human workers in the future, current real-world implementations of such adaptive work systems and advanced assistance systems are limited and may still be considered far-fetched (Kaasinen et al. 2020). In contrast, the replacement of humans by cyber-physical systems for highly standardized tasks will certainly become reality, thus creating fears of unemployment and limited job opportunities in the workforce (Adam et al. 2018). To acquire the necessary capabilities for the newly developing task environments, workers will require skill development programs with a particular focus on continuous learning (Gorecky et al. 2014; Bonekamp and Sure 2015; Longo et al. 2017). While these trainings provide opportunities for self-development, the constant need for learning also places additional demands on workers and can raise concerns about not being able to keep up with new requirements (Kadir and Broberg 2020). Moreover, the integration of humans in CPPS can also have detrimental effects on human job characteristics. While cobots can reduce physical strain by supporting humans in handling heavy objects, the close interaction of humans and machines also evokes new safety concerns (Kadir et al. 2019). Regarding system automation, increasing the automation level of a production system can move the human's role away from active control to passive monitoring, introducing the risk for automation complacency and deskilling (Bainbridge 1982; Parasuraman and Manzey 2010; Wickens et al. 2015). The changing balance between physical and cognitive tasks can also lead to cognitive overload when the required information is not provided to the worker in a suitable manner (Dombrowski and Wagner 2014; Czerniak et al. 2017; Kong 2019). Finally, the omnipresent collection of data in CPPS can threaten the privacy of the employees when personal information is stored and analyzed (Bonekamp and Sure 2015; Mannhardt et al. 2019).

The changing role of production workers in the transition to an IoP-based production ecosystem has led many researchers to suggest a stronger consideration of the human factor in this line of research (Romero et al. 2016b; Pacaux-Lemoine et al. 2017; Kadir and Broberg 2021; Nitsch et al. 2022). However, the amount of research that considers the human role in the future of production is still limited (Kadir et al. 2019; Sgarbossa et al. 2020; Sony and Naik 2020; Neumann et al. 2021). This is concerning, as a human-centered work design approach will be crucial to ensure that the upcoming transformation of production systems will in fact enable the improvement of human work characteristics and that threats to human job quality and job security are averted. Thus, only by considering the human early on in the development, the deployment of new technology will benefit human performance and well-being, ensuring organizational profitability (Dul and Neumann 2009) and preventing the erosion of anticipated profits due to poor system design (Rose et al. 2013).

To contribute to the body of research on the human-centered design of work systems shaped by the IoP, we present selected research addressing different levels of work design. To structure the individual research contributions, we follow the model of human-centered work design proposed by Mütze-Niewöhner and Nitsch (2020). The authors differentiate four levels of work design: (1) the work task, (2) the working conditions, (3) the organizational level, and (4) the supra-organizational level (see Fig. 22.1). Whereas the work task level addresses the interaction between the worker, with her/his individual characteristics, needs, and expectations, and technical systems to fulfill the task goal, the second level encompasses general conditions that influence this interaction. The higher levels leave the focus of

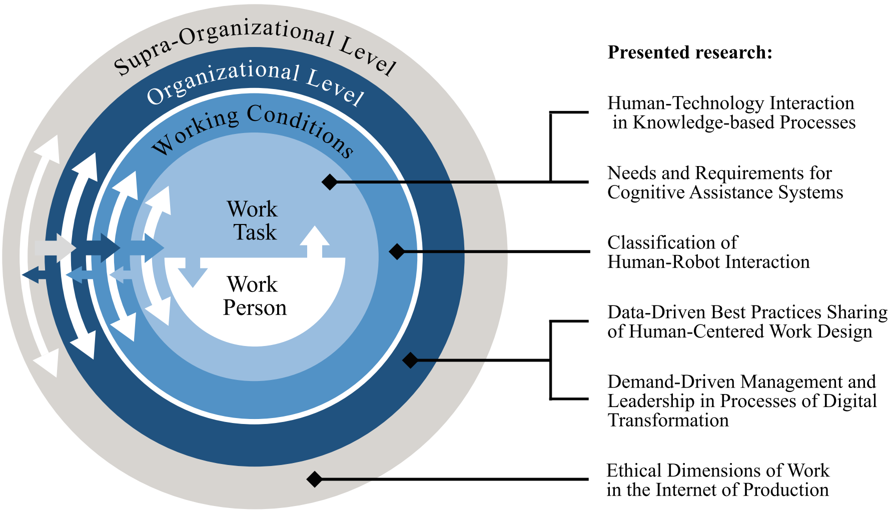

Fig. 22.1 Levels of human-centered work design, adapted from Mütze-Niewöhner and Nitsch (2020, p. 1198), as the structure for the selected research topics presented in this chapter

individual work systems and concentrate on strategic and cultural changes in work design within organizations, as well as on the discussion of work design principles that takes place in a societal and economic sphere. By presenting research across the various levels of work design, we seek to motivate researchers and practitioners to consider the transformation of work systems and human work in the course of implementing the IoP and to highlight the range of design dimensions that need to be taken into account.

22.2 Work Task Level: Human-Technology Interaction in Knowledge-Based Processes

Work tasks incorporating disruptive technologies such as artificial intelligence, collaborative and autonomous robotics, or augmented reality, face two major hurdles: the goal-oriented, successful technical implementation and the acceptance of the worker. In terms of technical implementation, production companies often face challenges with regard to data scarcity, possibilities for data collection, and methods for data exploitation. Additionally, difficulties may occur relating to the material processed, the optimization of production parameters, or logistics. To ensure the acceptance of the workers, it is essential to consider their concerns, wishes, and requirements, such as usefulness, fun, trust, previous experience, and knowledge (Frazzon et al. 2013).

When developing work tasks and the associated work systems, it is thus crucial to take a technology-centered as well as a human-centered perspective. This applies in particular to processes of which the outcome is heavily dependent on humans and their expert knowledge, both in work tasks that require largely manual labor (e.g., assembly, post-processing) and in work tasks with high cognitive demands (e.g., planning, design). However, the knowledge usually remains only with the respective expert, because (especially in SMEs) little to no documentation or knowledge management is implemented (Durst and Runar Edvardsson 2012). This can limit the competitiveness of companies as experts and their knowledge become scarce once senior employees leave the company or retire. Accordingly, it is necessary to extract, store, and transfer expert knowledge, for which both physical and cognitive support can be useful (Lewandowski et al. 2014; Brillowski et al. 2021a).

One industry that is strongly affected by the growing shortage of skilled workers and the associated loss of expert knowledge is the composite industry. The automation of composite part production is not worthwhile in all cases, for example, when a high amount of flexibility is required or if a part's geometric complexity is too high (Fleischer et al. 2018). Thus, two use cases in the composites industry are investigated regarding human-technology interaction: (a) human-robot collaboration in composite part production and (b) user-centered selection and planning of composite production processes.

To overcome the balancing act between requirements from technology and people in these use cases, we measured acceptance and user factors within usability studies. As a theoretical basis, the Technology Acceptance Model (TAM) is used to investigate perceived usefulness and perceived ease of use as well as attitude towards use, behavioral intention, and the actual use of the technology. Furthermore, the factors hedonic motivation, trust in automation, fun, mental/physical effort, and perceived autonomy when using automated systems are investigated (Davis 1989; Lee and See 2004; Bradshaw et al. 2005).

The two use cases are presented in more detail below.

22.2.1 Human-Robot Collaboration in Composite Part Production

Automation of composite part production is very complex due to the use of limp textiles and is therefore associated with high investment costs and a loss of flexibility. This applies in particular to composite parts with high complexity and the need for class A surfaces. Therefore, almost every second composite part is manufactured in elaborate manual processes, even though the needed experts are rare and expensive. Up to now, only laser projectors have been used as an assistance system to support these manual work tasks. Using these laser assistance systems in composite part production can result in timesaving of up to 45% and increases in the positioning accuracy of the textile layers. While these effects are especially applicable to the support of inexperienced employees, an increase in efficiency and high acceptance for the system can be noted for all employees, from laymen to professionals (Dammers et al. 2020b).

In order to further support workers and thus retain expert knowledge, we investigate how manual work tasks in composite production can be performed with the help of human-robot collaboration. Thereby, the work task is divided between human and robot based on complexity and experience, so that part quality and worker ergonomics are improved. For this purpose, robot tools for draping and handling were developed so that the efficiency and effectiveness of the process can be increased. During tool development, special attention was paid to work safety and technical limitation (robot payload and range) (Dammers et al. 2021).

Within a usability study ($N = 21$), the tools developed are generally perceived as valuable, so that the robot is regarded as a technical assistant performing the given collaboration task well. No dependence of the worker's satisfaction on the collaboration type, i.e., the degree of autonomy from the human perspective, can be observed. Low mental and physical challenges are indicated for the studied tasks. In general, autonomy and control are perceived as positive as are ease of use, trust, and hedonic motivation. However, usage intention for human-robot collaboration within composite production is rated positive but rather low, which can be attributed to the simplicity and low complexity of the examined tasks. A detailed description of the usability study can be found in the publication (Dammers et al. 2022).

Future research will therefore aim at further optimizing human-robot collaboration with respect to the factors of usage intention and usability. For this purpose, it is necessary to investigate the production of composite parts with a higher degree of complexity and more difficult work tasks. In addition, more suitable interfaces for robot operation will be developed, e.g., voice control or hand/food switches. Furthermore, the aforementioned technologies are to be combined in one workstation to enable more intuitive operation and execution. In order to secure expert knowledge for composite part production, the imitation of human movements by robots is also pursued so that the knowledge is collected, saved, and can be transferred by the supporting systems. For that purpose, artificial intelligence approaches will be investigated, e.g., imitation learning, learning from demonstration, and behavior trees.

22.2.2 User-Centered Selection and Planning of Composite Production Processes

Planning of production processes for composite parts is responsible for up to 70% of manufacturing costs (Ehrlenspiel et al. 2020). To minimize production costs and to comply with shortening product life cycles, an efficient and systematic planning of production processes is necessary for companies to remain competitive. However, existing planning methods for conventional materials like metals or wood cannot be applied to composites due to changing material properties during the production process (Brillowski et al. 2020). Therefore, the first approaches were developed to foster a systematic process planning. While these approaches increase effectiveness and efficiency, the accompanying methodologies and especially the developed decision supporting tools lack user acceptance (Brillowski et al. 2021b).

As a consequence, we investigate how decision support systems for production planning have to be developed to ensure a high level of acceptance among users. As planning decisions depend on a multitude of influencing factors, we intend to apply artificial intelligence for planning and examine its influences on user acceptance as well (Brillowski et al. 2021a). For this purpose, we developed two decision support systems based on different approaches. One app focuses on user-centered design and makes suggestions that can be rejected by the user. The second app integrates an optimization model, giving the user a mere supporting role. In the course of a user study ($N = 17$) we investigated, how usability, acceptance, trust in automation, performance expectancy, planning efficiency, and objectivity are perceived among domain experts (Brillowski et al. 2022; Zarte et al. 2020). The user-centered approach achieved the highest scores for usability and acceptance as well as performance expectancy, planning efficiency, and objectivity. In regards of trust in automation, users trusted the optimization-app most. However, in some cases, this leads to blind trust, not critically questioning the given results and neglecting crucial tasks, as participants expect the optimization app to relieve them from these tasks. Due to the non-existent transparency of the decision process, the optimization approach achieved an overall insufficient user acceptance. We conclude that automation can help to foster trust and acceptance. However, there is a degree of too much automation, which absolves the user of his responsibility. More detailed information on the user study can be found in the referenced publications. For future work, we want to research the optimal degree of automation to keep the user engaged on the one hand and to support them in the best possible way on the other hand .

22.3 Work Task Level: Needs and Requirements for Cognitive Assistance Systems – Towards Effective and Trusted Interaction

Increased information and automation through the digital transformation of production will significantly influence people's work tasks in CPPS, what their needs are for information, explanation, and decision support, and how future industrial workplaces and user interfaces must be designed (Brauner et al. 2022; Kadir et al. 2019; Neuman et al. 2021; Pinzone et al. 2017).

Despite the increasing possibilities of automation and data-driven optimization technologies in the IoP, humans remain one of the most important factors for the flexibility of production systems. Due to the changing socio-technical work systems, it is necessary to consider the needs and requirements as well as the skills of employees, which they will have to relearn or adapt and expand their knowledge. However, so far there is a lack of knowledge about the optimal trade-off between productivity goals, technical requirements, and the integration of user needs (Zarte et al. 2020). To improve the productivity of production processes and at the same time the acceptance of employees, extensive considerations are necessary for the design of cognitive assistance systems. In this section, we approach this challenge from the perspective of later users. Therefore, we present three studies which demonstrate important challenges as well as acceptance-relevant factors in the context of human-robot collaboration that have to be considered for a successful change of the socio-technical systems.

Cognitive assistance systems are technical systems that process information and support workers in performing their tasks and to improve their skills (Schlick and Trzcieliński 2016). The kind of support they can provide is divided into three different processing steps (Stair and Reynolds 2020), referring to the detection and recognition of tasks (1. task perception), assessing and generating tasks (2. task decision), and exporting the task (3. task execution). When designing new industrial user interfaces, it is important that they support cognitive tasks. However, the affective dimension must also be taken into account. A new system may be technically better, but if employees do not trust it, it will be used reluctantly or not used at all and thus cannot unfold its potential.

To study the affective dimension and task perception of cognitive assistance systems, we investigated moral decision-making in the context of human-robot and human-autonomous vehicle collaboration. A detailed description of the study can be derived from Liehner et al. (2022). In three different scenarios (production logistics, medical, and autonomous driving), participants ($N = 43$) could decide between assigning a task to an automatic agent or performing it manually depending on costs or possibly faulty automation which could result in damage to property or personal injury. The results indicate that both context and risk significantly impact people's decisions. The higher the perceived sensitivity of the context, such as in a medical context, the stronger the tendency to perform the task manually and avoid any personal harm. In addition to ethical and legal perspectives on automation and the interaction with robots (human-robot interaction = HRI), these findings suggest studying individual and contextual factors that influence trust in automated systems.

Considering the above-mentioned study about decision support systems for production planning (Brillowksi et al. 2022), we looked at it from a social accepted instead of a technical perspective. The process of task decision portrays an example for a cognitive assistance system. It supports by assessing and generating tasks. For an effective interaction it turned out that factors such as usability, speed, and functional superiority are relevant. Furthermore, trust was a decisive factor. However, considering that trust is evoked through transparency and comprehensibility of the suggested solutions, it was overshadowed by acceptance relevant features such as performance expectancy. Further information about the study can be extracted from Brillowksi et al. (2022).

For future work, focusing on the needs and requirements for cognitive assistance systems, it is therefore important to develop an understanding for the context of work and, of course, for the prospects of users (Courage and Baxter 2005). Moreover, a participatory design approach is recommended with frequent evaluation cycles as well as the users' involvement from the beginning and taking all stakeholders into account. Thus, the system functionality and interface match with the user and reduce interaction errors and unnecessary frustration.

For a task execution process of a cognitive assistance system, we investigated the collaboration between worker and cobot in textile production concerning different degrees of autonomy (low, middle, high) from the human perspective (Dammers et al. 2022). The technical perspective regarding the tools used in this study was already described in the previous section about human-robot collaboration in composite part production.

The results highlight that the interaction with a cobot generally promotes satisfactory task performance and high perceived control, with low perceived autonomy across all types of collaboration. The study further found ease of use, hedonic motivation, and experience in textile processing as factors relevant to acceptance. More detailed information on the study can be found in the publication of Dammers et al. (2022). Since autonomy and control are related to a higher task performance and job satisfaction (Deci and Ryan 2008), we propose to adapt robot movements and workflows to the workers and to set up intelligent interfaces for better individual robot support. Additionally, the results indicate that participants with little experience in textile processing rate the usability higher. An explanation for this could be that more experienced people already have familiar work processes. Therefore, they consider the cobot as a limitation of their freedom and intervention possibilities. For increasing the usability and acceptance of HRI, the workflows and robot operation should be optimized and the user diversity factors should be examined in more detail.

Across all studies, we identified trust, acceptance, and usability as essential factors for a positive attitude toward cognitive assistance systems which facilitate work tasks. Since in all processing steps of a cognitive assistance system data and information are collected, processed, stored, and evaluated, it is necessary to focus on the acceptance of data sharing especially out of a worker perspective. Therefore, there is a need to investigate information in future studies referring to the willingness to disclose personal data in an increasingly interconnected smart factory. Only broad empirical investigations with regard to the design of cognitive assistance systems can improve acceptance, trust, and usability and consequently increase the productivity of production processes.

22.4 Working Conditions Level: Classification of Human-Robot Interaction

In the production of the future, human-robot interaction (HRI) and collaboration (HRC; commonly viewed as a particular case of HRI) will gain importance (Matheson et al. 2019). For this reason, a deep understanding of this type of work system and a way to synthesize and analyze it is important. In order to achieve this, a suitable HRI framework is among the things required.

Existing HRI frameworks can be grouped according to which aspects they classify: There are classifications (1) by function (e.g., Parasuraman et al. 2000), (2) by degree of robot autonomy (e.g., Parasuraman et al. 2000) and (3) by work- and spatial distribution (e.g., Otto & Zunke 2015). In addition to these main categories, there are other approaches, mostly targeting specific applications, which will not be discussed further here. Onnasch and Roesler (2021) provide a detailed overview of existing HRI frameworks.

To survey HRI-relevant research activities in IoP, a survey was conducted, and from its results, requirements for HRC were elaborated in a workshop. In a subsequent literature search, no framework could be found that fulfills all these requirements of HRI applications of the production of the future, as they are being researched in the IoP. The problem, in particular, is that existing frameworks cannot map the entire range of applications across many disciplines. Moreover, many of them are designed for HRI within a social context and not for the industrial production domain.

Accordingly, it was decided to adapt and extend the framework of Otto and Zunke (2015): In addition to the dimension “HRI level,” the two dimensions “precondition & implication” and “data sources” were added (see Fig. 22.2; Baier et al. 2022).

The framework uses (shape- and) color-coded dots that indicate strengths and weaknesses and can also be labeled with text to represent information in the grid fields.

Dimension HRI level. For the distinction of the HRI level, the overlap of the workspaces of human and machine is used – from (physically) separated to completely overlapping. In addition to the categories in the original framework,

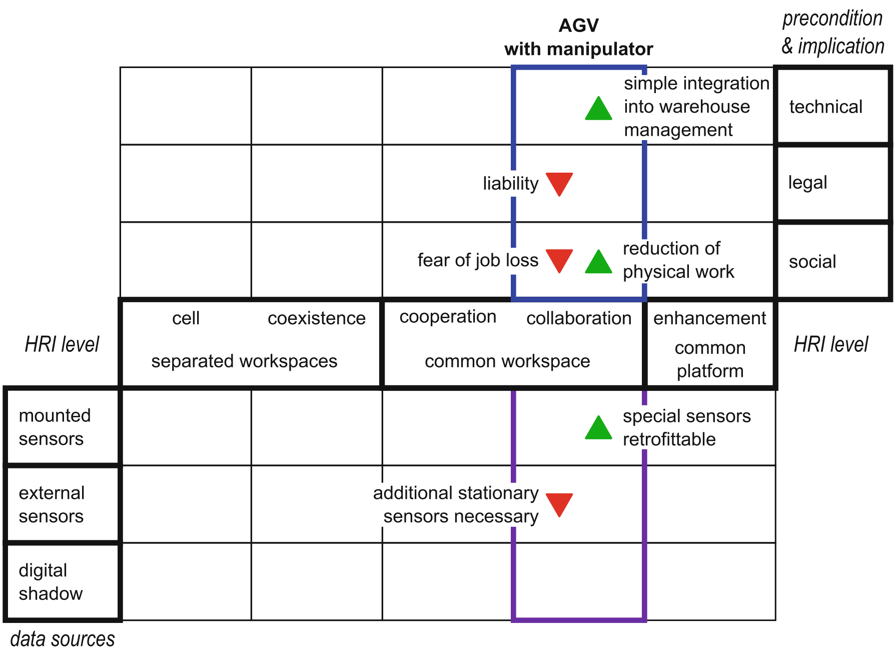

Fig. 22.2 Extended human-robot interaction (HRI) framework (Baier et al. 2022) – example filled in

another category has been added that refers to a common platform, as needed for wearables, prostheses, or exoskeletons.

Dimension Precondition and Implication. The preconditions and implications of the HRI application are described here from technical, legal, and social perspectives. For example, a technically well-engineered solution that is also legally compliant can nevertheless trigger a problem from the social perspective in the form of dissatisfaction due to a feared job loss among employees.

Dimension Data Source. For many HRI applications, the source of the data is relevant. The distinction between mounted and external sensors as well as digital shadow/digital twin reflects the dependence of the HRI application on external infrastructure. For example, mounted sensors as the primary data source allow for more independent operation from data infrastructure, but this can be at the expense of quality.

Figure 22.2 shows a completed schematic: In this fictitious example, the introduction of an automated guided vehicle (AGV) with manipulator in a warehouse is being planned. The shape- and color-coding allows for a quick overview and simplifies the identification of problematic and unproblematic areas of this solution. The obstacles apparently lie in the legal area as well as in the acceptance of the robots by the employees. Except for the fact that a sensor infrastructure has to be installed, there is no technical reason not to implement the robots.

With the HRI framework developed, it is now possible to analyze (classify) and synthesize (design) HRI as it pertains to production of the future and relevant research. Hence, the framework can also be used for the human-centered design or optimization of an HRI work system. For this purpose, special requirements resulting from the technologies used in a sector or specific legal regulations within it, as well as the demographics of the employees can be taken into account. Solutions can also be compared by filling in multiple schemas. Here, the degree of detail can be freely selected according to the needs. The clear presentation makes it easy to communicate proposals and decisions to superiors or the workforce.

Validation with respect to applications outside the IoP is still pending. In addition, more in-depth research in the Precondition and Implication dimension is planned – especially with regard to the social perspective.

22.5 Organizational Level: Data-Driven Best Practices Sharing of Human-Centered Work Design

As the intended result of an IoP, CPPS enable the continuous automation of production processes while simultaneously increasing productivity. Nevertheless, human work remains a key factor for productivity due to the specific capabilities of humans and the associated flexibility (Ansari 2019). To realize this productivity, employees are exposed to various forms of work demands during production processes. In addition to enabling cyber-physical collaborations, the increasing digitalization of work processes offers the opportunity to record relevant data and to use this information for the assessment of these work demands (Neumann et al.

2021). The analysis of these data can thus be used to secure competitive advantages by using a data-based comparison of the production processes to identify optimum configurations (Schuh et al. 2021).

In accordance with this optimization principle, the Best Practice Sharing Tool presented in the ▶ Chap. 16, "Managing Growing Uncertainties in Long-Term Production Management" was developed within the IoP. Despite the relevance of knowledge as one of the most important resources in the industrial context, the transfer of production knowledge for the realization of a continuous learning process between employees presents a challenge for manufacturing companies (Ferdows 2006). The complexity of this transfer is increased by the distribution of knowledge in global production networks, making this field of research particularly relevant (Yang et al. 2008). While the evaluation of production processes in terms of productivity has been elaborated, the necessary consideration of human workload in this data-driven optimization approach for production process design remains a challenge. Accordingly, with the objective of initiating workplace improvement measures across the production network, corporate data are used to identify comparable production processes in terms of human work characteristics and identify best practices by comparing human work demands, extending the current version of the Best Practice Sharing Tool.

For the Best Practice Sharing Tool, two key building blocks were developed to identify knowledge transfer opportunities: First, the data-based identification of comparable production processes, and second, the development of an assessment methodology to identify trigger points for the need of knowledge transfers based on productivity performance indicators. To identify comparable production processes, processes are represented based on a morphological box by linking the constituent product and resource characteristics. Subsequently, the description of the production processes is transferred into a digital shadow, which is used for the data-based formation of clusters of comparable production processes. By means of a cluster analysis, the metric characteristics can be divided into different proficiency categories (Schuh et al. 2020). As a result, performance differences within clusters of comparable production processes can be identified. These clusters are transferred into a dynamic assessment system to identify trigger points for determining knowledge transfer needs in the global production network. The operator can then interact with the tool to initiate the deployment of improvement measures. These are derived from the system-based identification of ideal characteristics. The application thereby serves as a decision support tool for initiating a best practice-sharing approach in the context of production processes in global production networks (Hast 2021).

The transfer of the described method to the human-centered focus requires the capability to compare production processes with each other. Since the criteria used for the elaborated method are only of economic or technological orientation, it is necessary to define the constituting characteristics of production processes from the workers' point of view. Here, the model of human-centered work design by Mütze-Niewöhner and Nitsch is applied to structure the approach (see Fig. 22.1). The Best Practice Sharing Tool as a decision support system for managers, supporting them in the identification and implementation of measures to reduce the work demands on production workers, is itself located on the organizational level. The individual level subsuming the worker, the work task, and the working conditions serves as a framework for the constituting characteristics of production processes from a human-centered perspective.

Based on a systematic literature review, criteria and description factors of production processes with a human-centered focus are identified (Fettke 2006). The comprehensive database of indicators from this research area is used to compile a long list of criteria in terms of the frequency of occurrence, relevance to the focus of observation, and possible quantification or evaluation for the later identification of trigger points. The indicators can then be classified according to the applied model of human-centered work design.

As the goal of the criteria list is to compare the design of production processes, the worker level is excluded from the analysis as it relates to the individual characteristics of the respective workers. The level of the *work task* includes the execution of the production process and the associated demands on the employee. Thus, the work demands of the process execution by means of intensity, duration, or complexity, but also, for instance, local vibrations and other emissions are included. *Working conditions* represent more general conditions, encompassing job design as a station-specific perspective and the work environment as a macroscopic perspective. The workplace is considered from an ergonomic point of view with regard to working position and accessibility or work equipment. The work environment describes cross-workstation characteristics and thus represents criteria such as noise, air conditions, lighting, or temperature.

Based on the general assignment of the indicators of the long list, a criteria short list is developed via further classification, consolidation, and relevance consideration. Eventually, the short list can be used to compare production processes from a human-centered perspective in order to provide the basis for the identification of best practices through an assessment system of human work demands factors for production processes in global production networks.

Following the presented approach, the current research project focuses on the elaboration of the criteria long list through a comprehensive examination of existing research. After the assignment to the three defined domains, the criteria short list can be elaborated in order to present a practicable data-based method for the comparability of production processes with human-centered focus based on the application of corporate data in several iteration and optimization loops.

22.6 Organizational Level: Demand-Driven Management and Leadership in Processes of Digital Transformation

Krcmar (2018) emphasizes four elements of digital transformation processes that must be considered. From his perspective, transformation processes are (a) inevitable, (b) irreversible, (c) characterized by a high degree of speed, and

(d) accompanied by a high degree of uncertainty in their execution (Krcmar 2018). For companies, therefore, the main question should not be how they can decouple themselves from the coming change, but how they can actively shape the transformation process (Krcmar 2018). In this context, the management of digitization processes seems to play a special role. Hoberg et al. (2018) indicate that digital transformation projects are characterized by a high degree of social complexity that needs to be managed actively. They conclude that digitization projects, face the challenge of having to overcome rigid or at least existing and thus mostly established corporate structures (Hoberg et al. 2018). Correspondingly, Hoberg et al. (2018) found in a quantitative study 84% agreement among participants regarding the statement that change management skills are of great importance for the organizational transformation and that management support is required at various management levels (Hoberg et al. 2018). His result is affirmed by research on organizational change projects, showing that support from management is necessary to ensure the targeted allocation of financial and human resources required for the change process (Premkumar and Potter 1995). In addition, unforeseen obstacles that arise during the change process can be overcome more easily if the transformative processes are actively managed (Hwang et al. 2004). Recapped, digitization represents a major challenge for organizations, as it affects the working environment of employees as well as employees' requirement profiles. Moreover, it must overcome organizational structures and processes to be implemented sustainably. Consequently, it results in the need for organization-specific and thus demand-oriented management, to better counter the effects of the change process on the organization and its people. To ensure this, an analysis of the realities on the technical, structural, and personnel sides represents the first step.

The need for a requirement-specific approach becomes even clearer when reflecting industry-specific characteristics. The manufacturing sector is confronted with special requirements that intensify, e.g., element (4), namely a high degree of uncertainty, of Krcmars' (2018) formulated aspects of transformative processes. Production data, which is to be shared if an organization adheres to the idea of an IoP, often represent the core value. As a result, the willingness to share these data is low since sharing such valuable data triggers feelings of uncertainty, which was confirmed by a qualitative study of the Research Group Gender and Diversity in Engineering (GDI) of RWTH Aachen University in 2020/2021. In addition, established and therefore partly old plants and production systems represent the central value of companies in the manufacturing sector. Yet, digitizing these plant systems can only be realized with a corresponding effort. Furthermore, management must consider the people in change processes, diverse target groups, resulting diverse demands and fears that arise. This diversity results on the one hand from the different areas of activity, namely in production itself as well as in the administration and management of the organization. On the other hand, diversity results for example from the individual affinity for digital solutions and age diversity in the workforce. Consequently, diversity must be actively considered when implementing corresponding digitization projects, to increase the acceptance of digital strategies and technologies in the context of change processes (Steuer-Dankert 2020).

To cope with the challenges mentioned, different management methods such as *new and digital leadership* are currently being discussed. Research has shown that success in organizational aspirations toward a productive digital transformation is positively correlate to the enablement, development, and implementation of such a form of managemental leadership (Sprenger 2017; Kane et al. 2018; Abbu et al. 2020; Araujo et al. 2021). Sprenger (2017) sees the future viability of companies in their ability to discuss probable and improbable scenarios and to generate the necessary redundancy through a diversity of opinion. Likewise, he sees companies as well prepared that encourage stubbornness and a spirit of contradiction. For Sprenger (2017), *transformational leadership style*, therefore, represents the ability to create an organization that is willing and able to change, especially in this context of digitalization. So, the active enablement, development as well as implementation of a new and digital style of managemental leadership can be seen as crucial to guarantee the successful satisfaction of transformative demands in digital contexts.

Linking a further management style with digitalization, Araujo et al. (2021) define *digital leadership* in its most fundamental sense as "the use of digital assets of an organization to achieve business goals at both organizational and individual levels" (p. 46), while referring to Dimitrios et al. (2013) and Thomson et al. (2016). What seems to be the most crucial aspect in the light of the addressed challenging demands of digital transformation is the interactive and behavioral cultural change that such a form of leadership brings into the organization and its internal processes; something that is highly needed within such processes of digital transformation (Kane et al. 2018; Abbu et al. 2020; Araujo et al. 2021). What is meant by that is that *digital leadership* or *digital leaders*, as role models, should actively help the organization to detect and evaluate the given demands of the transformation and to change the organization towards these demands of digitalization by showing, guiding, and enabling: flexibility/agility, curiosity, openness, a willingness to learn, an open, egalitarian and non-hierarchal style of communication and decision-making, innovative entrepreneurial tendencies, trust, and credibility as well as transparently laying out a vision and purpose of the ongoing change processes (Kane et al. 2018; Abbu et al. 2020; Araujo et al. 2021). Doing so is not only positively related to the organizations' success in terms of digitalization (Araujo et al. 2021), but also to the psychological well-being of employees, like in this case the leaders/managers themselves, that are involved in these transformative processes (Zeike et al. 2019).

Taken together, all of this highlights that if organizations want to satisfy the demand of an increasingly digitizing industry and, thereby, be successful in terms of implementing digital innovations or strategies as, e.g., needed in the context of the IoP, there is also the need to actively implement a demand-driven, evaluative, and reflective management that is able to deal with the arising diverse needs and challenges on a human as well as on a technical level.

22.7 Supra-Organizational Level: Ethical Dimensions of Work in the Internet of Production

Work takes up a large amount of time in people's lives as their main occupation and activity, and is often a source of their identity, stability, and safety. Changes in the conditions of someone's work thus reflect not only their immediate daily activities, but also often their orientation in life, their sense of identity and social status, and consequently their overall happiness and other ethical values, such as dignity, autonomy, and freedom (European Group on Ethics in Science and New Technologies 2018). The main source of the changes of work conditions are technologically mediated changes, namely via automation and digitization. These necessitate ethical reflection on the impact of those changes on human flourishing in their everyday life (Danaher 2019). It is vital to consider those ethical dimensions early on, together with engineers and social scientists to be able to assess, evaluate, and guide the design and implementation challenges of such technology.

In the IoP, we closely cooperate across disciplines to achieve these aims through exchange of perspectives and ideas. This way, ethical reflection and research is informed of the latest technological developments, while also being able to offer assistance and guidance for engineers and scientists in their work. Next to the more fundamental changes in people's understanding of their own work in light of automation and digitization, there emerge more practical challenges to the way people work. Increased digital capabilities of surveilling workers in their actions and overall performance poses the question of privacy at work (European Group on Ethics in Science and New Technologies 2018; Königs 2022). How much is an employer entitled to control and supervise their employees' actions? With both new tools of surveillance and a more digitized workplace, the work performance of an employee can be measured and supervised to a previously unseen, intrusive degree.

Another issue of changing work environments in the IoP are the ever more distributed and thus shared decision-making processes between humans and machines. Our previous understanding of technology placed agency exclusively in the hands of human agents. Technology thus far has been seen as a mere range of tools to achieve self-set aims. However, the increased and further increasing sophistication of automated and autonomous processes of technological systems in workplaces not only makes it difficult to determine where human decisions played into an automated decision-making process, but also may make these decision-making processes necessarily cooperative in the first place. For the IoP, this was identified as a key challenge for the future of work (Nitsch et al. 2022).

It is important to consider that some decisions may not be made by sole human decision-making but are predicated on decision-support systems that pre-select evidence and with that recommend certain paths of decision-making the human decider has little to no control or knowledge of. If, for example, automated systems seek out, evaluate, and on this basis recommend certain paths of action, it will increase the burden of proof of humans when disagreeing with those recommendations. The question arises of just how much autonomous machines can support human decisions without influencing them to the degree it affects our autonomy.

From this development, distributing responsibility in human-technology interactions emerges as an ethical challenge. With more sophisticated and autonomously behaving machines, the bearers of responsibility become less clear. When doubts emerge of how much meaningful human control can be exerted in these processes, just how much should a person be held responsible for the outcome of such a process (Königs 2022)?

These considerations pose genuinely new and hard questions regarding the future of ever more automated work environments and the social sustainability of these developments. Ethical considerations are needed at every step of these developments, as they change the meaning of work as a source of identity, stability, and human flourishing. In the coming steps, we aim to contribute to these developments through analyses of concepts of autonomy, freedom, and manipulation in those more automated work environments. Notably, we aim to incorporate the normative dimensions of the concept of sustainability in both its environmental and social dimension into these analyses and assessments.

22.8 Conclusion

Realizing the IoP will lead to fundamental changes of how humans work in future socio-technical production systems. To ensure that this digital transformation enables the anticipated improvements in both overall productivity as well as workers' physical and psychological well-being, it is of most importance to consider the human factor as early as possible, implementing a human-centered work design process. The selected research from the IoP presented here highlights the multitude of factors and levels in the design of work systems that needs to be taken into account. For example, the development and deployment of advanced human-machine interfaces such as human-robot collaboration or AI-based cognitive assistance systems require the context-specific analysis of human factors such as trust, acceptance, and usability. Furthermore, the consideration of such interfaces needs to incorporate influences from the present working conditions, including characteristics of the workplace and the work environment. These work system design processes must, in turn, be guided by human-centered approaches on the organizational level. For example, processes should be implemented that enable a large-scale human-centered analysis of work system design. Moreover, the associated transformation poses new and diverse requirements on leadership, raising the need for demand-driven, evaluative, and reflective management. Finally, all these developments must also be considered from an ethical perspective, evaluating how technological changes affect central human needs such as privacy and autonomy. It is important to note that, while these aspects have been discussed in separate sections here, companies that strive towards an IoP will have to consider all these factors and levels of work design at the same time in order to remain competitive for an increasingly mobile workforce in a global market. This emphasizes the challenge that companies face and that must be overcome to ensure the desired outcomes of this digital transformation. To support the companies in this transformation, further and continuing research efforts on the human-centered work design of future socio-technical production systems are required.

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Design Elements of a Platform-Based Ecosystem for Industry Applications

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Abstract

Many companies in the Industry 4.0 (I4.0) environment are still lacking knowledge and experience of how to enter and participate in a platform-based ecosystem to gain long-term competitive advantages. This leads to uncertainty among firms when transforming into platform-based ecosystems. The article presents a structuralist approach to conceptualize the platform-based ecosystem construct, giving an overview of the literature landscape in a model bundled with unified terminology and different perspectives. The holistic process model aggregates the findings of 130 papers regarding platform-based ecosystem literature. It consists of 4 phases and 16 design elements that unify different terminologies from various research disciplines in one framework and provide a structured and process-oriented approach. Besides, use cases for different design elements were developed to make the model apply in an I4.0 context. Use Case I is a methodology that can be used to model and validate usage hypotheses based on usage data to derive optimization potential from identified deviations from real product usage. By collecting and refining data for analyzing different manufacturing applications and machine tool behavior the importance of specific data is shown in Use Case II and it is highlighted which data can be shared from an external perspective. Use Case III deals with strategic modeling of platform-based ecosystems and the research identifies control points that platform players can actively set to adjust their business models within alliance-driven cooperation to create and capture value jointly. Use Case IV investigates the status quo and expectations regarding platform-based ecosystems in the field of laser technology with the help of structured expert interviews. Overall, this chapter presents a framework on industrial platform-based ecosystems that gives researchers and practitioners a tool and specific examples to get started in this emerging topic.

23.1 Introduction

The rise of interconnected businesses participating in a platform-based ecosystem has induced a redesign of existing business models in various industries and technology sectors. Starting with telecommunication networks, platform-based business models are prevalent in many industries today; especially in the online gaming industry (Boudreau and Jeppesen 2015) or social networks (Li and Agarwal 2017). As per our understanding ecosystems consist of independent yet

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interdependent actors who interact to generate a joint value proposition. Actors include (multiple) platforms, users, and complementors. A platform is the technology that allows the efficient creation of many options by producers and/or users. Platforms act as an intermediary facilitating exchange/transactions between different actors and/or serve as a foundation on top of which other firms develop complementary technologies, products, or services (Adner et al. 2020; Jacobides et al. 2019; Parker and van Alstyne 2018). Many companies lack knowledge and experience of how to enter, participate, and position themselves in a platform ecosystem to gain long-term competitive advantages. The promises of Industry 4.0 lead to increased cross-domain collaboration and industrial data sharing within an open ecosystem based on underlying platform business models. For example, when shifting from a product system to a platform-based ecosystem, firms lack knowledge of how resulting value is captured and shared in the ecosystem. To cope with interdependencies in the ecosystems, firms need to assess whether they must build up new competencies (Stonig et al. 2022). So far, only a few companies in an Industry 4.0 environment have experience in platform design, leading to uncertainty among firms regarding platform-based ecosystems.

The literature on platforms and ecosystems has grown enormously in recent years. However, the existing literature is currently very scattered across many disciplines (Rietveld and Schilling 2021). Researchers have mostly investigated terms of platform and ecosystems isolated within their disciplines, delivering insights from an isolated point of view. Especially in management, information systems, and engineering disciplines, the research is further based either on platform or ecosystem literature, with a lack of integrating platform and ecosystem aspects. Further, existing research does not give a holistic overview of platform-based ecosystems, as researchers mostly focus on specific aspects. This work fills the gap by combining research from different disciplines, defining and organizing relevant aspects of platforms and ecosystems from the perspectives of the ecosystem, the platform organizer, and the complementor and placing them in a process-oriented framework. We combine these research strings, giving a holistic overview of relevant literature related to platform-based ecosystems. Past platform and ecosystem literature usually discusses specific aspects, either of platforms or ecosystems. McIntyre and Srinivasan (2017) focus on the view of industrial organization economics, technology management, and strategic business perspectives of platform-mediated networks. The research of Hagiu (2014) analyzes four strategic challenges regarding multisided markets that are the number of sides to bring on board, design, pricing structure, and governance rules. Jacobides (2019) deals with the emergence of ecosystems and clarifies the differences from other forms of governance. The work of Rietveld and Schilling (2021) provides a literature review focusing on platform competition and providing an overview of key questions around network externalities, platform ecosystems on corporate level, heterogeneity, and value creation and capture. Rietveld and Schilling (2021) cover individual aspects on both, platform and ecosystems, yet not classified within a holistic process model. Our process model builds on the paper of Rietveld and Schilling by adding further important aspects to their described key themes as well as showing how individual elements are interrelated and fit into an overall process.

23.2 Description of the Process Model for Platform-Based Ecosystems and Industry Applications

The process model was developed using a hybrid approach combining both common literature analysis and new machine learning methods for further verification. Using a Boolean search query string regarding titles and publication outlets, a comprehensive list of around 400 academic papers could be identified via Web of Science. To be included in the list, at least one of the following words had to be in the title: "ecosystem," "platform," "network effect," "complementor," "sided market," "network externality," "network effect" or a combination between the phrase's "innovation" and "ecosystem" or "platform," "strategy" and "ecosystem*" or "platform," "open" and "ecosystem" or "platform." To ensure an interdisciplinary approach, we included journals known for their research on platforms and ecosystems from management, information systems, and engineering disciplines. Subsequently, all papers were manually reviewed in aspects of relevance and contextual fitness. For a further verification of the literature, we used the machine learning software ASRreview which deploys learning techniques for an efficient screening of titles and abstracts (Van de Schoot et al. 2021). The software was given a training set of 40 relevant and 10 irrelevant articles which was used to learn and select the most relevant articles. The result was 130 relevant papers, which were the basis for our model. From the literature selection, we synthesized 16 design elements for platform-based ecosystems and allocated at least one design element per paper. To ensure a structured process, we defined four phases, namely "Strategy," "Design & Entry," "Within-platform competition," and "Between-platform competition" and assigned each design element to one of the four phases. Starting point for the definition of our phases and design elements were the four structural factors from Gawer (2014) and Parker and van Alstyne (2018): "governance," "organizational form," "capabilities," and "interfaces." The "organizational form" and "capabilities" are in our "Strategy" phase, in which firms need to clarify questions of how to play and use an ecosystem. The governance dimension is central part for all phases after the strategy was clarified. The last factor "interfaces" was divided into the phases "Within-platform competition" and "Between-platform competition."

Our process model bundles and aggregates the findings of selected papers regarding platform-based ecosystem literature. It consists of 4 phases and 16 design elements that unify different terminologies from various research disciplines in one framework (Fig. 23.1). Each design element is backed up with relevant articles and key questions for three different perspectives are elaborated, namely the ecosystem, the platform orchestrator or complementor. The first "Strategy"-phase consisting of five design elements defines how to play and use an ecosystem. Key questions are described per design element which should be asked before companies enter the ecosystem, either as a platform orchestrator or complementor. The second phase "Design & Entry" describes the design and scale of a platform within in ecosystem by bringing others on board and is based on three design elements. The "Within-platform competition"-phase deals with the competition and collaboration with

Fig. 23.1 Platform-based ecosystem process model

complementors on the platform to maximize value creation and capturing of one's ecosystem. The last phase "Between-platform competition" which consists of five design elements clarifies questions of how to compete and collaborate with other platforms to ensure platform attractiveness and survival.

23.2.1 Strategy

Being part of a platform-based ecosystem is a strategic action, opening new ways of capturing value. To be successful in a platform-based ecosystem, actors of the ecosystem therefore need to define a shared value proposition with their future stakeholders. Both, the platform orchestrator and the complementors, need to outline how to capture value for themselves while serving the focal value proposition of the ecosystem (e.g., Autio and Llewellyn 2015; Zhang et al. 2020; Clarysse et al. 2014). Role positioning refers to the organizational governance on an ecosystem level. Platforms take different roles to follow the value proposition. The positioning (dominant vs. niche) of the platform in the overall ecosystem needs to be addressed by the platform orchestrator. From the complementor's point of view, the number of platforms should be discussed as part of the overall ecosystem strategy (Chen et al. 2021). The pre-defined shared value proposition of a platform-based ecosystem requires resources and capabilities to be implemented successfully. All players of the ecosystem should bring needed capabilities to support the overall value creation. They also need to identify capabilities that already exist, and capabilities that need to be assured by other actors (e.g., Hagiu 2014; Henfridsson et al. 2021). Part of the overall ecosystem strategy is the question of which existing intellectual property or industry standards can be leveraged by the platform orchestrator as well as the complementors. Value co-creation in an ecosystem builds on interdependencies as well as complementarities of the respective goals of the participants (Bogers et al. 2019). Defined interdependencies and complementarities shape the ecosystem strategy and the outcome of value capture. Participants of the ecosystem question how to influence complementarities and interdependencies in the ecosystem (e.g., Alexy et al. 2018; Autio and Thomas 2018).

23.2.2 Design and Entry

The degree of openness chosen by participants of an ecosystem defines the level of cooperation with external players. Hence, ecosystem resources can be shared in order to foster cooperation, using, e.g., an open-source license approach. However, shared ecosystem resources are vulnerable to being strategically exploited. The platform orchestrator must balance the optimal degree of openness to spur innovation while still ensuring control. Complementors need to manage the adequate access and decision rights that are crucial to be successful on the platform (e.g., Ondrus et al. 2015; Cenamor and Frishammar 2021). Network effects describe how the number of participants of a platform can impact the value generated for the participants of the platform. The question for both platform orchestrator and complementors is how to induce new network effects or, if not possible, how to use existing ones (e.g., Panico and Cennamo 2019; Markovich and Moenius 2008; Kim et al. 2014; Allen et al. 2022; Gregory et al. 2021). The decision of pricing accounts for the dynamic interaction between each side of the ecosystem. The pricing structure of platform-based ecosystems should balance the value captured for each player, in order to keep all players on board. The platform orchestrator, on one hand, specifies which side to subsidize by themselves to bring all sides on board. Complementors, on the other hand, need to be clear about which pricing structure and pricing mode to accept (e.g., Economides and Katsamakas 2006; Dushnitsky et al. 2020).

23.2.3 Within-Platform Competition

Vertical integration addresses the decisions of which activities are performed by the platform provider and which by the platform complementors, then defining how the efforts of the players are integrated into a coherent whole (Wang 2021). To achieve platform health over time, fast and sustainable growth is shaped by the decision of how to share profit for the platform with multiple stakeholders. As a platform orchestrator, the challenge lies in determining the maximum share of profit for the platform without alienating complementors. Complementors will determine the minimum share of profit that is still acceptable (Oh et al. 2015). Boundary resources play a critical role in managing the tension between an ecosystem owner and independent external players. The main challenge for the platform orchestrator is how to obtain a competitive advantage with strategic openness. Complementors set which kind of boundary resources can be used (e.g., Woodard 2008; Eaton et al. 2015; Ghazawneh and Henfridsson 2012).

23.2.4 Between-Platform Competition

To orchestrate outbound communication and cooperation with external players, platform owners should define which kind of bottlenecks can be removed in order to foster progress and growth (e.g., open innovation by removing technological bottlenecks). Therefore, control points are crucial to secure profits and competitive advantages, managing how the network operates and how other players can participate in the ecosystem. The main challenge for the platform orchestrator and the complementors is to identify bottlenecks that can be resolved (Hannah and Eisenhardt 2018). The importance of the number as well as the nature of complements (heterogeneity) are crucial in terms of shaping the ecosystem structure. Leveraging complementor dynamics plays an important role in gaining a competitive advantage. Hence, the platform orchestrator needs to solve the trade-off of focusing on many complements vs. securing exclusive marquee complements (e.g., Rietveld and Eggers 2016; Panico and Cennamo 2020). Multi-homing describes the decision about the exclusiveness of complementors and/or users on one hand, and the affiliation with other platforms on the other hand. From the perspective of a platform orchestrator, the question of how multi-homing can be prevented plays a central role. Complementors need to think about how costly it is to affiliate with other platforms. The main challenge of platform envelopment describes how actors of different platform markets can combine their functionalities to leverage existing user relationships and expand into other markets. The platform orchestrator as well as complementors need to address the question with whom to compete and cooperate (e.g., Adner et al. 2020; Ansari et al. 2016). Cooperation and competition need to be balanced over time. Therefore, it also has to be specified if competition takes place on specific layers and/or in between platforms.

To transfer the process model into an I4.0 context, four different research topics are defined as use cases for different design elements.

23.3 Use Case I: Use of Product Usage Information to Identify Innovations

Product development in the machinery and plant sector is currently facing a variety of challenges. As in many other industries, the entry of new competitors and the emergence of overcapacities have led to an increase in the intensity of competition. Accompanied by an increase in price pressure, this has led to a shift in market power to the customer side (Schuh and Riesener 2018). At the same time, the lifetime of a product on the market is decreasing. While this used to be the case primarily for consumer goods, the lifetime of industrial products, as in machinery and plant engineering, is also becoming shorter and shorter (Michels 2016). For the companies in the market, it is important to take the impact on a necessary reduced time-to-market and shorter innovation cycles into account (Schuh and Riesener 2018). In addition to price and quality, the short innovation time thus evolved into the criterion for success (Ehrlenspiel and Meerkamm 2013). In this context, the development costs for products with overloaded product functions or product functions that are rarely used in the usage phase raise exponentially (Schuh et al. 2020). Based on the initial situation described above, the aim is to increase the effectiveness and efficiency of research and development (Schuh 2013). Particularly in the context of the innovation process, companies are more than ever confronted with the challenge of completing the activities from idea generation to market launch as quickly as possible and with scarce resources, while at the same time ensuring the highest possible probability of success (Gommel 2016). The rapid translation of an identified customer need into a market-ready solution has become one of the key success factors in competition (Michels 2016). Development activities, especially for new products, must therefore be focused on those product functions that have a positive influence on the fulfillment of customer needs.

In contrast, product development faces the challenge that companies lack knowledge about which product functions the customer actually needs and to what extent. While the range of functions in most products is constantly increasing, it is still the task of humans to anticipate and develop them (Michels 2016). Similarly, a consultation of future customers does not prove to be effective, since they usually do not yet know how the product will be used in the specific application. Development activities and focus are therefore based on assumptions about later product usage and the corresponding customer needs. If customer feedback is taken and used to focus product development, it is usually unstructured and isolated feedback from distributors or service partners based on warranty cases, complaints, or product recall (Abramovici and Lindner 2011).

With regard to the initial situation and challenges presented, the transformation of machines and plants from mechatronic to cyber-physical products offers enormous potential. Cyber-physical machines enable information from product usage to be generated, recorded, stored, and evaluated by means of sensors (Hellinger 2011). The recorded information can be used to examine how the functions of the machine are used in order to derive valuable findings for innovations in the next product generation. Assumptions about later product usage, which were made due to a lack of knowledge during product development, can be verified by the recorded product usage information.

This potential was exploited in the presented use case by developing a methodology for identifying innovation potential through the analysis of product usage information. The methodology pursues the objective of systematically formulating product development assumptions as hypotheses and testing them based on recorded product usage information to derive innovation potential for the next product generation.

In the context of the platform-based ecosystem process model, the methodology can be assigned to the "Strategy"-phase and specifically to design elements "Value creation & Capture" and "Resources & Capabilities," as it deals with general added value that can be derived from usage data. This is particularly evident in the development and elaboration of the individual phases of the methodology presented later. Value is generated on the part of the machine and plant manufacturer by the possibility of better addressing the customer needs, which can lead to an improved market positioning and an increased competitiveness. Simultaneously, the customer receives a product with an improved cost-benefit ratio in the long term, as fewer or even unused functions and the associated higher costs are eliminated. Due to the level of detail of the methodology it is shown what kind of information and capabilities are required and could be provided by stakeholders in a platform-based ecosystem to generate the value. In general, it can be stated that within the implementation of the methodology in the context of a platform-based ecosystem, further design elements and their contents need to be elaborated. Nevertheless, primarily in terms of an exemplary use case, the method illustrates a way to generate value from data that can be shared via a platform.

The methodology consists of four steps (Fig. 23.2). In the first step, the usage cycle of the machine is systematically described and it is determined where the user can influence the machine during usage. Based on this, relevant product usage information to be recorded is derived in the next step. In the third step, the assumptions about the product usage are formulated as so-called usage hypothesis

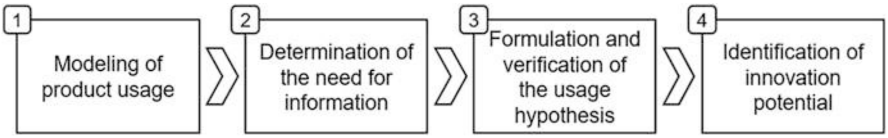

Fig. 23.2 Four steps of the methodology for the identification of innovation potential

and verified by recorded product usage information. Finally, innovation potentials for the next machine generation are derived from deviations between the usage hypothesis and real product usage. The four steps are explained in detail below.

The aim of the first step is to model the usage cycle of the machine as a basis for the further methodology. In accordance with systems theory, the usage cycle is defined as a structural system in which the elements of the system are not considered detached from the context, but only in their interdependencies with other system elements (Ropohl 2009). In order to develop a suitable method for modeling these elements, at first various requirements for the modeling were developed. In addition to other requirements, the modeling of the usage cycle should represent the states of the product functions, their functional attributes, and the transitions between the product functions, the so-called transitions. Various existing modeling methods, such as state machines, Petri nets, and UML, were analyzed with regard to these requirements, and suitable elements were adopted.

Subsequently, different types of variability were identified, which means the changeability of the modeled elements due to external influence by the user. It was determined that the user can influence the duration of the functions, control the characteristics of the functions and select between different functions or transitions. Based on modeled elements as well as types of variability, the need for relevant product usage information to be recorded was derived. The minimum, average, and maximum attributes, the frequency of use of various functions and transitions, and the usage duration of functions were among others identified as relevant information.

Afterward, the usage hypothesis can be defined based on the modeled usage cycle, the identified variabilities, and required information. The usage hypothesis comprises the assumptions about the respective information that describe the state of the modeled elements in usage. The one-sample t-test was identified as a suitable test procedure for the subsequent verification of the usage hypothesis on the basis of recorded product usage information (Hedderich and Sachs 2018). This test can be used to identify significant deviations between the usage hypothesis and the actual usage of the machine in the usage cycle.

In order to convert the identified deviations into innovation potential, it was first assumed in the sense of the finality and causality of human action that the user pursues a specific goal in use with all deviations (Hartmann 1951). Deviations between usage hypothesis and real product usage were therefore first clustered into generic use cases and linked to possible targets in the usage of the machinery. From the analysis of the use cases, various innovation potentials could be derived, such as the elimination of a function, the change of a solution principle, or the expansion of the possible attribute value. In order to enable efficient processing in the subsequent product development, a recommendation for action was elaborated for each innovation potential.

With these four steps, the methodology addresses the challenges presented above in the development of machines and plants. Through the targeted recording of relevant product usage information, innovation potentials can be efficiently derived and the speed and success in the development of innovations can be increased.

23.4 Use Case II: Potentials of Knowledge Sharing with Platform-Based Ecosystems in the Context of Machine Tools

For the analysis of various manufacturing applications in machining, data can be collected and refined from different sources along the digital process chain. Manufacturing execution systems (MES) are widely used in industry to document discrete-event information on production such as throughput times, set-up times, or possible quality problems and their respective causes. However, to gain specific insights into the behavior of the machine tool, its components, and the manufacturing process itself, the acquisition of continuous and high-resolution data is required. Modern CNC machine tools allow accessing data from machine internal sensors in the control cycle. This involves recording high-frequency sensor data from the machine controller such as axis positions, drive currents of the axis, spindle speeds and spindle positions, as well as discrete-event messages as the active tool or NC line (Brecher et al. 2018).

In addition to machine-internal data, external sensors such as force, acoustic emission, or vibration sensors can be applied to the machine tool to monitor machining operations. Especially the measurement of the occurring process forces is of crucial importance due to the high sensitivity and rapid response to changes in cutting states (Teti et al. 2010). In practice, it is not the data from machine-internal or external sensors during the machining process itself that is of interest, but the underlying knowledge that is worth sharing from an external perspective. Therefore, raw data must be refined into characteristic values to share them between different participants within a platform-based ecosystem. This form of data exchange enables participants to map correlations based on this knowledge without having to generate the underlying raw data themselves. Sharing this knowledge in the form of recommendations in turn offers potential for optimizing machining processes. In this context, combining raw data from the machining process with domain-specific models enables the necessary data refinement by addressing known issues in machining as quality defects, wear condition of tools or components and creating a Digital Shadow of the respective object of observation (Brecher et al. 2021a).

Brecher et al. (2019) and Königs and Brecher (2018) describe an online material removal simulation that generates a Digital Shadow of the workpiece based on process parallel recorded machining data and available manufacturing metadata. This digital workpiece can be used to assess the manufacturing quality and derive further information about the engagement situation during machining. Based on the resulting availability of information on the engagement situation and process forces this information is mapped on the used tools to monitor the wear condition during machining (Brecher et al. 2022; Xi et al. 2021). Monitoring the wear condition facilitates maintenance measures by estimating the remaining service life. In addition, findings on correlations between the usage of tools in machining processes achieved workpiece quality and the resulting tool wear can be leveraged for a more efficient and sustainable use of tools.

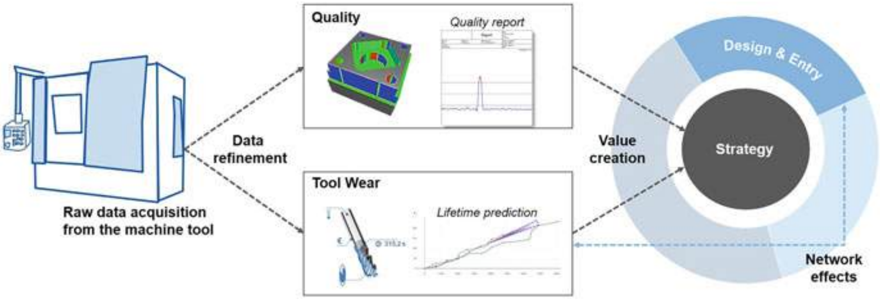

Fig. 23.3 Integration of the machine tool context in the platform-based ecosystem process model

The described use case for collecting and refining data in context of machine tools can be assigned to the "Strategy"-phase of the platform-based ecosystem process model. Refining raw data from machining processes creates added value by gaining knowledge with regard to parameters relevant to practice and thus enables leveraging existing resources and capabilities in the machine tool environment. After this form of value creation, the characteristic parameters can be used across platforms and thus network effects from the "Design & Entry" phase can be exploited. The integration of the machine tool context into the process model is shown in Fig. 23.3 on the example of workpiece quality and tool wear.

The success and crisis resistance of digital business models is demonstrated in particular by examples from the media and entertainment industry (Vonderau 2017; Winter 2017). Adapting these digital business model approaches on the machine tool industry raises different challenges. Companies underline their high customer orientation and focus on technology and product. Therefore, the central value proposition is still the physical machine tool. In some cases, digital add-on applications are offered as services for machine tools, but these are not integrated into a service-oriented value chain and thus often cannot lead to additional financial benefits. In conjunction with a high level of complexity in the provision of services in machine tool manufacturing, this results in a further cause for the lack of digital business models such as platform-based approaches (Copani 2014; Kamp et al. 2017).

To address the stated challenges, Brecher et al. (2021b) name two enablers for successfully implementing a digital business model. Examples from industry show that the basic technological enablers are in principle already in place. However, these individual solutions must evolve to cross-company platforms through standards and guidelines. Although companies face technological problems due to a lack of competencies in the digital domain, this is not the main obstacle for the implementation of these business models. Prevailing mindsets at the management level of manufacturers and users within the machine tool industry are of greater importance, particularly in the direction of the central value proposition and thus human enablers. In this regard, expert interviews conducted at the Laboratory for Machine Tools and Production Engineering (WZL) of RWTH Aachen University show that central questions regarding data security, cost transparency and calculability, liability and risk assessment, and dependence on third-party companies must be answered before using platform-based business models on the machine tool industry.

Generally, the pure adaption of digital business models from other industry on the machine tool context is not possible, as the stated challenges are not solvable this way. The platform-based ecosystem process model creates a methodological framework to develop possible solutions to face these challenges.

23.5 Use Case III: Strategic Modeling of Platform Ecosystems

Industry 4.0 as the fourth industrial revolution is based on the digitization of manufacturing processes. Collecting data throughout the processes not only create ample opportunities to improve efficiency and quality, but also enables the possibility to advance business models, e.g., through selling value-added services based on data generated at customers, or by creating new subscription models for machines based on this data. For instance, insights gained through using a machine tool at a company can be played back to the manufacturer to improve future machine generations. With these new business models, data-driven platforms emerge that trade machine data as good. However, these platforms pose major challenges for existing market participants. Not only do they have to update their machine parks to incorporate new smart functionality and deal with large amounts of data on the first place, but they do have to take strategic decisions on the fate of their organization's business model. Existential questions are, for instance, whether they should participate in the nascent data market, or whether they should create a data platform themselves, or join an existing data platform, possibly from a competitor. Data availability in platforms also opens opportunities for new members as complementors such as startups specializing in artificial intelligence (AI) products, as there is a low entry-barrier without investments in industrial hardware. Examples are service-oriented business models with multi-angular relationships between companies (Pfeiffer et al. 2017).

Yet, data-related ecosystems are highly complex regarding their operational and technical level of data management, service exchange, and IT security mechanisms. To shed light on these opportunities, we observed and analyzed the positioning of market players in the agricultural industry. The farming sector is dominated by a few large manufacturers with two market players in Europe and North America, respectively. In the 2010s, the market leader began with setting up its platform-based ecosystem including players in its supply chain as well as customers. Based on an extensive study incorporating the analysis of the strategy of an agricultural machine manufacturer (Van Dyck et al. 2020), we identified several control points that influenced their data strategy. We combine the findings of the study with strategic modeling with the conceptual modeling language iStar (i*) and the setting of control points (Koren et al. 2021). In the following, we present the resulting model. We then show how the strategic model can help organizations in finding their strategy in dealing with new data-driven ecosystems, by actively setting control points.

The large-scale study follows the suggestions for rigorous case study research by Yin (2018). To derive the model, we identified several stakeholders participating in the smart agricultural data platform and their goals. First, the Manufacturer delivers products and services to the farm. The Dealer provides, sells, and leases farm machines to a Contractor, that in turn cultivates the fields. The Farmer commissions the Contractor to efficiently raise living organisms for food or raw materials. A Farm Management Platform as new actor in the agricultural value chain integrates data from the farm. It also provides the entry point for complementors to offer new, innovative services to other stakeholders.

Figure 23.4 shows the conceptual model of the stakeholder relationships in the described agricultural data ecosystem following the iStar 2.0 modeling notation. It presents a view on the dependencies between the stakeholders. For instance, from center right to center left, a Farmer depends on a Manufacturer for machines. An example for a non-physical asset displayed in the model is machine data, which the Farm Management Platform depends on from the Contractor.

For organizations in a platform-based ecosystem, it is of high strategic importance to anticipate their future decisions at an early stage. Strategically, this is best done top-down, as actively placed management decisions. We therefore combine our strategic modeling with control points. They can be set to grant access or impose certain behavior (Eaton et al. 2015). Organizations can, for instance, set up control points, by adhering to certain technical standards. Platform operators, on the other hand, could introduce multi-homing costs to promote their own platform. A detailed discussion of the proposed control points is out of scope, the reader is kindly referred to an earlier publication (Van Dyck et al. 2020).

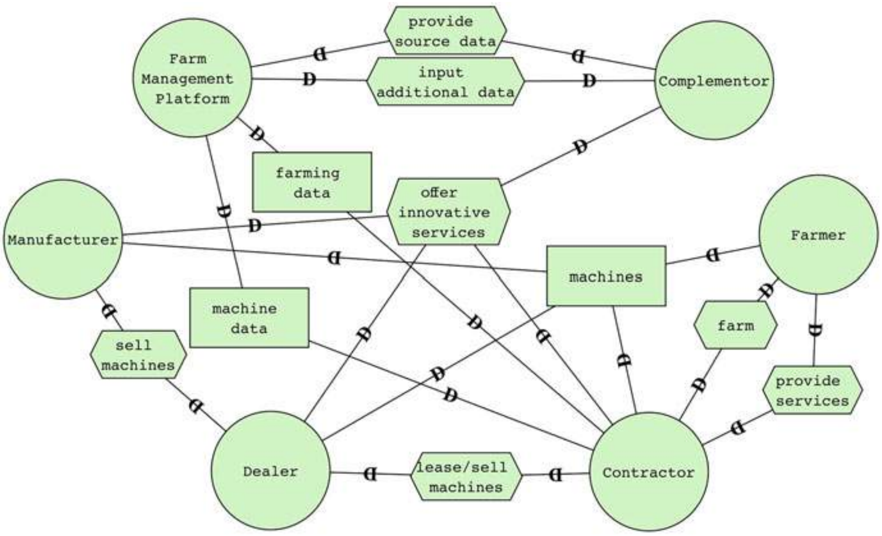

Fig. 23.4 Strategic dependency view of stakeholder relationships

The technological basis for autonomous data exchange between companies are interfaces. The platform thereby embraces standards that manage the interdependencies in the ecosystem (Thomas et al. 2014). While, for instance, the International Data Spaces Association introduced an architecture for data sharing between its members, it does not impose a specific format for the data objects. In the Internet of Production, we are exploring the notion of Digital Shadows as conceptual abstractions (Becker et al. 2021).

Platform ecosystems in industrial environments are challenging in terms of technology layers (Sisinni et al. 2018) and relationships (Schermuly et al. 2019). Potentials and risks need to be recognized in time, so that companies can take strategic decisions in advance. Our research portrayed above introduces two tools that can deal with the complexities: modeling using the i* language and control points. They are decision-making instruments to plan the next step within platform ecosystems. Regarding our process model for platform-based ecosystems, they are therefore tools located in the strategic core. Decisions on this strategic level have radiating effects toward the other phases. For instance, providing data access to industrial machines result in a strategic openness, with APIs as possibly boundary resources that platform players can actively set to adjust their business models to create and capture value jointly. The challenge is to identify and assess these opportunities early on. As a next step, we plan on providing an initial repository of available graphical representations and code structures to facilitate automated decision support for stakeholders. These design patterns could allow organizations to discover missing links and potential obvious options.

23.6 Use Case IV: Laser Material Processing Market Pull for Digital Platforms

Laser material processing is particularly predestined for close coupling to digital value chains. This is due to the unique properties of laser light (Poprawe et al. 2012). Like no other tool, laser light can be controlled extremely quickly and extremely precisely in space and time based on digital data (Hinke 2017). With the various laser-based subtractive and additive manufacturing processes (e.g., laser beam cutting, laser beam surface structuring, or laser-based additive manufacturing), it is thus possible to realize highly individualized components in very small quantities directly from digital data (Hinke et al. 2015; Gu et al. 2021; Poprawe et al. 2017).

Figure 23.5 shows the concept of Digital Photonic Production. The entire laser-based manufacturing process is directly controlled by digital data. Digital data or the digital shadow of the component to be produced (left) controls the entire laser processing system. This allows raw material (lower right) to be ablated, applied, or locally modified in the smallest 2D or 3D surface or volume units (lower center). Essentially, (i) laser beam source (power, time distribution), (ii) optical system (focal length, spot size), and (iii) beam guiding system (spatial distribution x, y, z) are controlled by digital data (Poprawe et al. 2018).

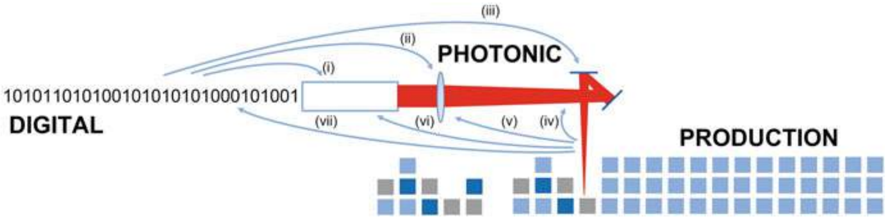

Fig. 23.5 The concept of Digital Photonic Production

At the same time, laser-based manufacturing processes can be adjusted and thus corrected extremely quickly and precisely during the manufacturing process. Typically, with optical sensors, large amounts of data can be recorded in high spatial and temporal resolution during laser manufacturing processes. Based on process understanding represented in Digital Shadows (reduced real-time process models) or on trained AI methods, it is possible to control the entire laser processing system and therewith the laser-based manufacturing process in real time. The blue arrows (iv–vii) in Fig. 23.5 represent these closed control loops (Knaak et al. 2018).

In many cases, manufacturing defects can be controlled before they lead to defective components. This is because the time scale with which a laser beam can be controlled is typically an order of magnitude smaller than the time scale with which the molten material typically moves. An incorrect energy- or heat-input during laser-based additive material processing can thus be corrected, for example, before the liquid melt solidifies in its final geometry (Knaak et al. 2021). However, the enormous technological potential of Digital Photonic Production can only be fully exploited if corresponding digital business models and platform-based ecosystem are developed and implemented. The photonics industry, which is characterized by many small- and medium-sized companies, is still struggling with the development of corresponding digital business models and platform-based ecosystem though (Poprawe et al. 2018).

Against this background, a survey was conducted in 2020 with 34 companies from the photonics sector. In addition, two workshops were held with senior representatives from these companies in 2020 and 2021. The various obstacles to the development and implementation of digital business models and platform-based ecosystems were discussed and analyzed in six small groups in each case. Based upon this, recommendations for the design of such digital business models and platform-based ecosystems were developed.

The study shows that a large majority of company representatives see a medium to high potential of artificial intelligence (80%) and digital services (74%). At the same time, a vast majority of companies complain of having no or too little in-house expertise and appropriately trained personnel in these areas. Especially in the field of AI, the internal acceptance of this technology is not yet very high. The study shows a very indifferent picture regarding the internal acceptance, particularly in the field of AI: the company's internal acceptance of AI is estimated to be low and rather low

Table 23.1 Results of a survey on the topics artificial intelligence (AI), digital services, and the according platforms

Question	Low and rather low (%)	Neither low nor high (%)	Rather high and very high (%)
How do you assess the potential of AI for your company?	20	20	60
What is your level of interest in participating in a collaborative AI platform?	20	40	40
What is your level of interest in AI education and training formats?	15	20	65
How do you assess the acceptance of AI within your company?	35	30	35
How do you assess the potential of digital services for your company?	26	5	69
What is your level of interest in participating in a collaborative digital services platform	26	10	64
What is your level of interest in education and training formats regarding digital services?	21	37	42
How do you asses the acceptance of digital services within your company?	26	22	52

(35%) as well as high and rather high (35%) with the same percentage. However, the internal acceptance of digital services is significantly better and is rated as medium to high (74%) by a majority of the surveyed companies (Table 23.1). Accordingly, the overwhelming majority has a medium to high level of interest in education and training formats in the field of AI (85%) and digital services (79%).

In the following expert workshops, two main challenges were identified, and corresponding solutions were proposed. The companies have broad domain know-how (laser technology), but according to their own statements hardly any AI-know-how or any know-how about platform-based ecosystems. Secondly, besides interest and expectations of the companies in the topics of digitization and artificial intelligence are great, AI and platform-based ecosystems are seen as a great opportunity, but also as a potential threat. On this basis, the following recommendations for the design of such digital business models and platform-based ecosystems were developed: (1) Analysis of examples from other industries on the use of AI and platform-based ecosystems and analysis of transferability to laser technology. (2) Development of transferable design and behavioral rules for dealing with platform-based ecosystems. (3) Development of transferable design and behavioral rules for dealing with multiple platforms simultaneously in the role of non-dominant designer. In a next step, we plan a detailed elaboration of our derived recommendations to facilitate the design and development of such digital business models and platform-based ecosystems in laser material processing.

23.7 Conclusion

Our process model provides an overview of the relevant literature regarding important design factors of platform-based ecosystem. Building up on the framework, academia can identify relevant areas for future research. Furthermore, a structured and process-oriented approach is given due to the division into phases, specific design elements, and key questions for different perspectives. The holistic process model helps managers to tackle all relevant aspects before entering in a platform-based ecosystem as platform orchestrator or complementor. Practical examples in the context of I4.0 are developed for different design elements and/or phases to make the model easy to understand and apply. The methodology from Use Case I can be assigned to the Strategy phase and specifically to the design elements “Value creation & capture” and “Resources & Capabilities,” since it deals with general added value that can be derived from usage data. At the same time, it generally shows how field data can be used in product development, but also which capabilities are needed. Research of Use Case II can be integrated into the “Strategy”- and “Design & Entry”-phases. In addition to showing which data can be shared from an external perspective, Use Case II demonstrates whether digital business model approaches from other industries can be transferred to the machine tool industry under the condition of data availability and expected challenges. Strategic modeling of platform-based ecosystems is shown in Use Case III and can therefore be understood as the connection of the central “Strategy” phase, with effects that radiate toward the other phases. Use Case IV can be assigned to the “Strategy”- and “Design & Entry”-phases. The research identifies the future potential and possible obstacles regarding platform-based ecosystems in the field of laser technology.

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