Chapter

Remote Management of Autonomous Factory

Yen Kheng Tan and Felix George

Abstract

In today's mass production era, the world is making things (products and systems) so quickly and systematically in huge volume. The demand for these products is very high and, at the same time, consumers are still in search for a need for making the production very personalized. Hence, the "one mold fits all" approach may not seem to be enough. The present approach is facing the lack of networking between the automation pyramid levels, that is, especially between enterprise resource planning (ERP) and manufacturing execution system (MES) layers and, in turn, communicating directly with the lower layers is not possible. This missing communication among the process equipment like machineries and field control systems like PLCs at the production shop floors implies that customization at the product layer for the consumer is still in progress in classical manufacturing. Mini-MES is a new concept being introduced here to solve the existing techniques reported in the literature and is followed by industry best practices. The novel mini-MES platform provides an avenue for the technology process level (the most bottom layer) to interplay interconnectivity and interoperability with its higher levels until the above pain points are addressed holistically. The chapter is going to focus mainly on the factory production of digital manufacturing and on describing the 3-Cs implementation plan, the enabling technology, and the achievable outcome ahead.

Keywords: factory cloud platform (FCP), autonomous factory, edge computing AI

1. Introduction

The smart manufacturing initiative from the industry transformation perspective is rapidly emerging in many parts of the world. Few notable smart manufacturing transformations leading the globe are the Chinese version of Made in China 2025, the German version of Industry 4.0, the United States version of Industrial Internet (Made in America), the Singaporean Smart Nation, and the UK/EU version of Future of Factory. Clearly, the global trend is pivoting toward the new era from the traditional mass ("Ford's") factory production, where a consumer-oriented low-volume, high-mixed demand and supply production would be the smarter way to build and make things [1].

In the factory, the manufacturing system is illustrated by the pyramid shown in **Figure 1**. At present, the production shop floor is already highly reconfigurable in its process level. This is possible, starting from the enterprise resource planning

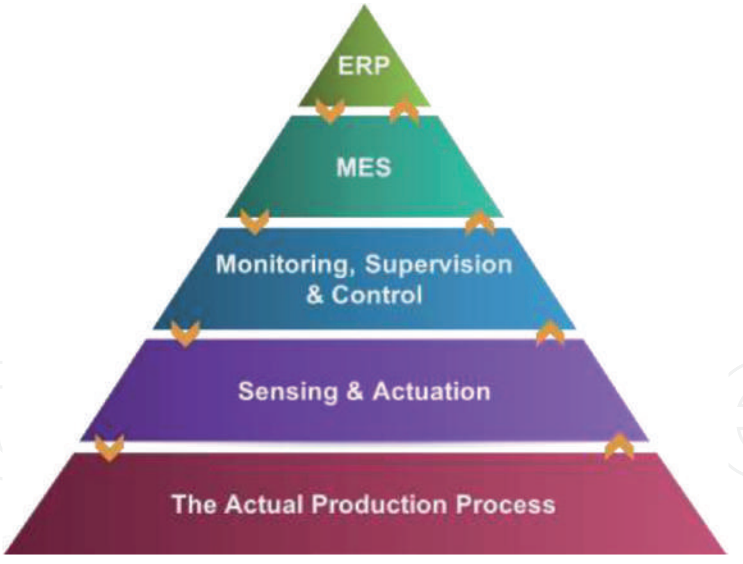

Figure 1.
The manufacturing pyramid—an overview of the existing production flow [2].

(ERP) layer, where process planning, operational management, etc. are interlinked. The manufacturing execution system (MES) layer is set to handle scheduling, dispatching production, etc. in a systematic manner. Monitoring, supervision, and control layer takes care of the real-time optimization and the advanced process controls. Sensing and actuation layer comprises the sensor readings' collection and manipulation of the production process. The final layer is where the actual production process exists.

In the above manufacturing pyramid diagram, few layers are already interconnected, but there are some layers which are independent silos. This is the pain point that is addressed through smart manufacturing, that is, introduction of the smart connectivity and interoperability throughout the layers. Various aspects need to be considered as it could be impossible to replace all the hardware in a manufacturing company to enable this. There could be some legacy systems as well which in itself would not be ideal to use in such an environment. By introducing the right cyber-physical tools and network connectivity, this can be achieved.

2. Digital manufacturing transformation

2.1 Mass production era

In today's mass production era, the world is making things (products and systems) so quickly and systematically in huge volume. The demand for these products is very high and, at the same time, consumers are still in search for a need for making the production very personalized. Hence, the "one mold fits all" approach may not seem to be enough. The present approach is facing the lack of networking between the automation pyramid levels, that is, especially between ERP and MES layers and, in turn, communicating directly with the lower layers is not possible. This missing communication among the process equipment like machineries and field control systems like PLCs at the production shop floors implies that customization at the product layer for the consumer is still in progress in classical manufacturing [3].

Recently, there is a strong pull to shift from the classical manufacturing/automation pyramid to the horizontal and vertical networking and to achieve the cyber-physical production systems (CPPS) as illustrated in **Figure 2**.

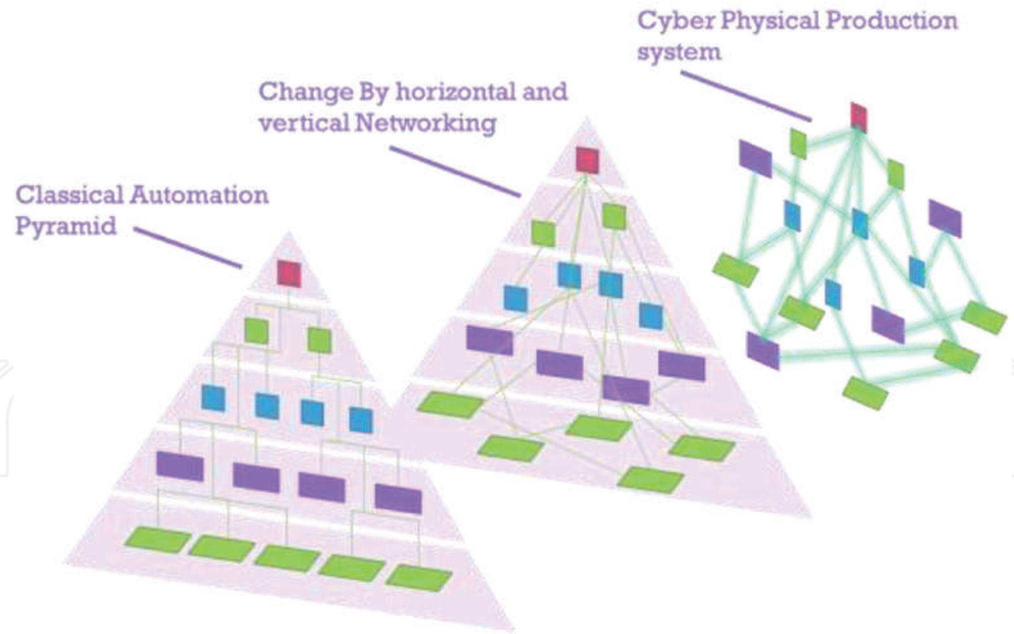

Figure 2.
The new paradigm of the manufacturing pyramid—an overview of the changed production flow.

The hierarchy arrangement of the automation pyramid is helpful for tracking the production status and for keeping proper process flow. Chaining the horizontal levels together adds value to the coordination and the vertical levels networks for more interconnection and cooperation. The full potential is attained when the boundaries are open. To reach this CPPS goal, one has to first identify and determine the associated pain points in order to enable the smooth transition:

1. Vast proprietary silos platforms/systems out there in the industrial systems.

2. Proper utilization of the available data.

3. Demand for higher response in terms of demand and supply of products in between the production line and the supply chain flow.

2.2 Digital manufacturing era

The CPPS is the backbone to the digital manufacturing era. The transition process from classical to digital manufacturing transformation requires a holistic platform of many Mini-MESs as shown in **Figure 3**. Mini-MES is a new concept being introduced by the authors to solve the existing techniques reported in the literature and is followed by industry best practices. The novel mini-MES platform provides an avenue for the technology process level (the most bottom layer) to interplay interconnectivity and interoperability with its higher levels until the above pain points are addressed holistically. There are four main aspects to be looked at and addressed, namely product, production, process management, and service manufacturing. This platform works hand in hand with the two upper layers to form the full CPPS as mentioned before in achieving the autonomous production factory. The rest of the chapter is going to focus mainly on the factory production of digital manufacturing and on describing the 3-Cs implementation plan, the enabling technology, and the achievable outcome ahead.

The 3-Cs implementation plans can be divided into three main parts. First is connecting to enable remote monitoring and management [5]. To truly remotely

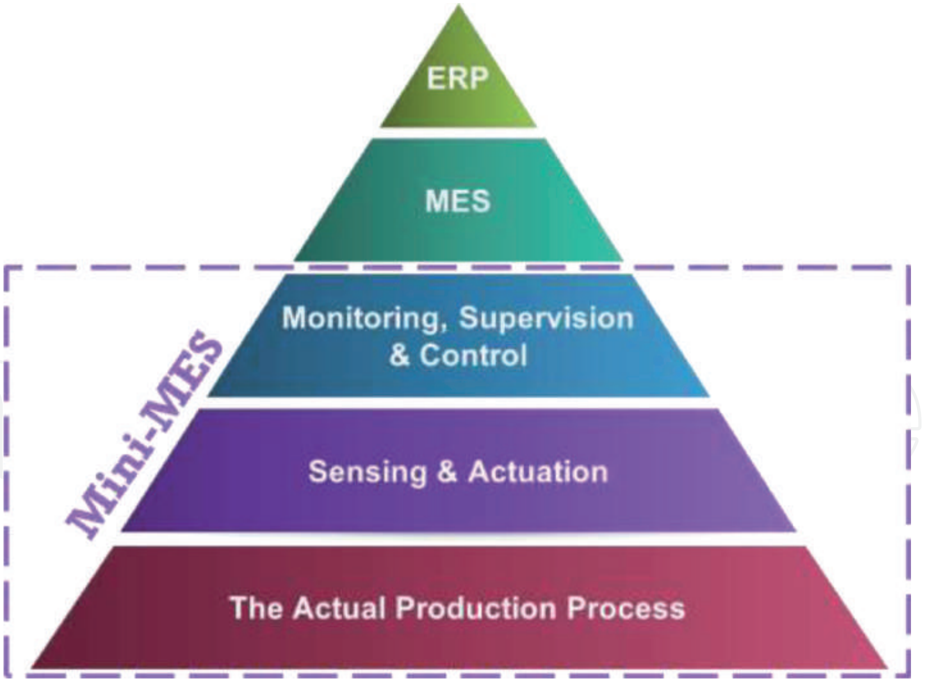

Figure 3.
Paradigm shift from classical automation toward interconnected smart systems [4].

manage the factory in real time, 5G technology has to be used since the specifications of 5G enable us to achieve a near real-time operation. The desired outcome is to achieve the large-scale deployment of remote autonomous control systems that are to be operated and managed seamlessly.

Second is computing at the edge. To implement as an aggregation point of the factory that holistically connects the dots of the individual levels of the automation pyramid and seamlessly control the communication protocols of devices and equipment of Siemens, Schneider Electric, ABB, etc. with a single common protocol. By doing so, any data point on the factory shop floor is available to the A.I. computation to develop the desired models and throughputs.

Third is collaborating/codeveloping with the domain experts. To leverage on the strong client records of experiences and add on to the implementation of the data platform to drive the traditional manufacturing market in a much faster and penetrable manner. Through the codevelopment process, the digital transformation of factory automation is going to accelerate tremendously while working closely back and forth with existing clients and leveraging on the existing manufacturing solution and the domain expertise.

3. Toward autonomous factory

As you may already realize, the global manufacturing trend is changing from the passive and reliant approach to a more demanding and intelligent way to manufacture produces. That is the smart factory (SF), which is rapidly growing and will be an anchor component of the digital manufacturing transformation journey. According to a financial report, it is expected that the SF market will continue to grow at a compound annual growth rate (CAGR) of 9.6% to reach around US$244.8 billion by 2024. In the case of the autonomous factory, it is projected to be one of the key enablers of these SFs for having the ability to be remotely operated and managed in the autonomous manner. Thanks to the data-driven platforms that are booming in from the digital space, the factory production can turn toward full automation and autonomy. It is expected to transform the traditional factory owners that produce in mass quantities with lots of manual workers into low-volume, high-mixture production with digital manufacturing technique.

The transformation will involve a set of digital technologies, including the Internet of Things (IoT), robotic and artificial intelligence (AI), into the implementation/upgrade for the factory modernization. With this, the new world of making things so agile in a flexible way, optimizing and integrating the system approach, and the great speed and accuracy are going to benefit and satisfy the fast consuming and highly personalized needs of the people (**Figure 4**).

Remote monitoring is a key aspect for an autonomous factory. For a manufacturing company to make money, it ultimately comes down to the number of products made. So, if there is an unscheduled downtime, the throughput of the production line reduces, and hence the company ends up making fewer products and thus loses money. We can overcome this by introducing a remote management solution. This would consist of a list of tools such as remote production monitoring, remote safety monitoring, machine learning, and artificial intelligence for predictive maintenance, which would address the problem even before they occur. As the solution is deployed, the owner will be able to see a reduction in operational costs and an increase in the equipment efficiency.

Remote management and monitoring had been available as a technology for the past decade or so, but somehow, the breakout year was never seen by the experts and observers. However, the situation is poised to change in today's scenario, with the new economic trends, transformed man power needs, and the availability of new technologies. During the global financial crisis, a lot of companies turned to lean staffing models. There is a certain lack of design and maintenance talents in many companies because of this. Coupling together with this is the retirement of the baby boomer workforce [6], who are extremely hardworking, which eventually led to a change in the demography of a factory floor. The new staff severely lack the decades of hands-on experience on the aging legacy equipment. They are also put under tremendous pressure to deliver a better throughput and more uptime and hence forcing the companies to remote monitoring and management.

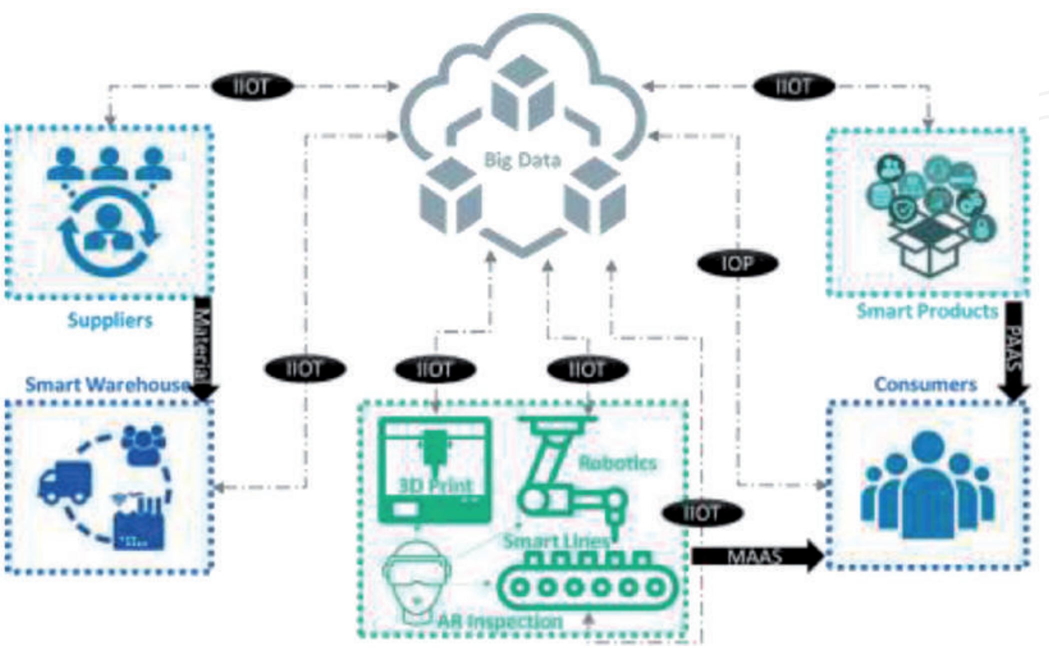

Figure 4.
Autonomous factory flow.

Another challenge we all know well is that the present manufacturing ecosystem is highly dependent on China, where most of the factories are located. China has a very strong fire wall, since they need to ensure their cyberspace is well protected, which is understandable. There is a great need for an IT platform that is equipped with the ability to capture true value creation from opening up the interrelationship between the nations like Singapore and China. The data exchange channel link has to be interlinked with minimum latency to empower an autonomous factory to interact on a real-time basis with its clients throughout day and night for 365 days without fail and to report machine health, process flow rate, and production status to the health diagnostic center for close and constant tracking outside China. Take for an example, there is this possibility with the use of the newly built Singapore and China data connectivity infrastructure of less than 60 ms latency between countries to enable online live communicating and producing of productions. This powerful data transmission exchange infrastructure will definitely enable an autonomous factory to work in a well-protected network environment.

The way things are bought and sold is going to change. It will go, way beyond buying from ecommerce platforms to making the products directly for the consumers. Take for an example, a production factory based somewhere in the middle part of China, in a city called Henan province, where there are a large varieties of machining/processing tools on the actual manufacturing shop floor. The digital manufacturing technology made by Printed Power (PP) Pvt. Ltd. (a company based in Singapore focusing on IoT and smart manufacturing) for the plant is an IoT-cloud platform that allows the remote manning, from the other parts of China or even from Singapore, of the Henan's factory production and maintenance as well as interconnecting the local resource planning ERP with the manufacturing execution system. The power of mini-MES (as illustrated in **Figure 3**) autonomous factory platform is to do away with: (1) restricted remote connectivity for the manufacturing solution to provide access to their local factory floor within China and (2) limited 24 × 7 real-time domain experts' monitoring and resource planning and managing of the factory production system.

In short, this proposed mini-MES autonomous factory platform is one of the first types of deployment in the world that compasses IoT-cloud cum edge computing technology to upskill the local manufacturing solution providers in serving their end manufacturing factory clients more effectively and efficiently. The autonomous factory software platform is performing three key functions: (1) to allow the manufacturing solution provider/system integrator to upgrade the traditional factory to be remotely access and control and (2) to support the manufacturing process/operation with the at-the-edge computers to do data compression for fast speed production and for onsite decision and execution for real-time factory throughput.

4. Technology enablers for autonomous factory

In this section, we will discuss the key technology enablers of an autonomous factory system. The discussion is going to surround on the digitalization tools, namely, the Internet of Things (IoT) hardware, the AI machine learning software, and the application design thinking/innovation needs. **Figure 5** illustrates an overview of the various technology enabling modules that apply to the autonomous factory context.

Among the many, the middleware or the firmware and operating system layers are the most important for the distributed edge computer network with AI processing at the cloud edge. As so, the edge computer becomes a crucial

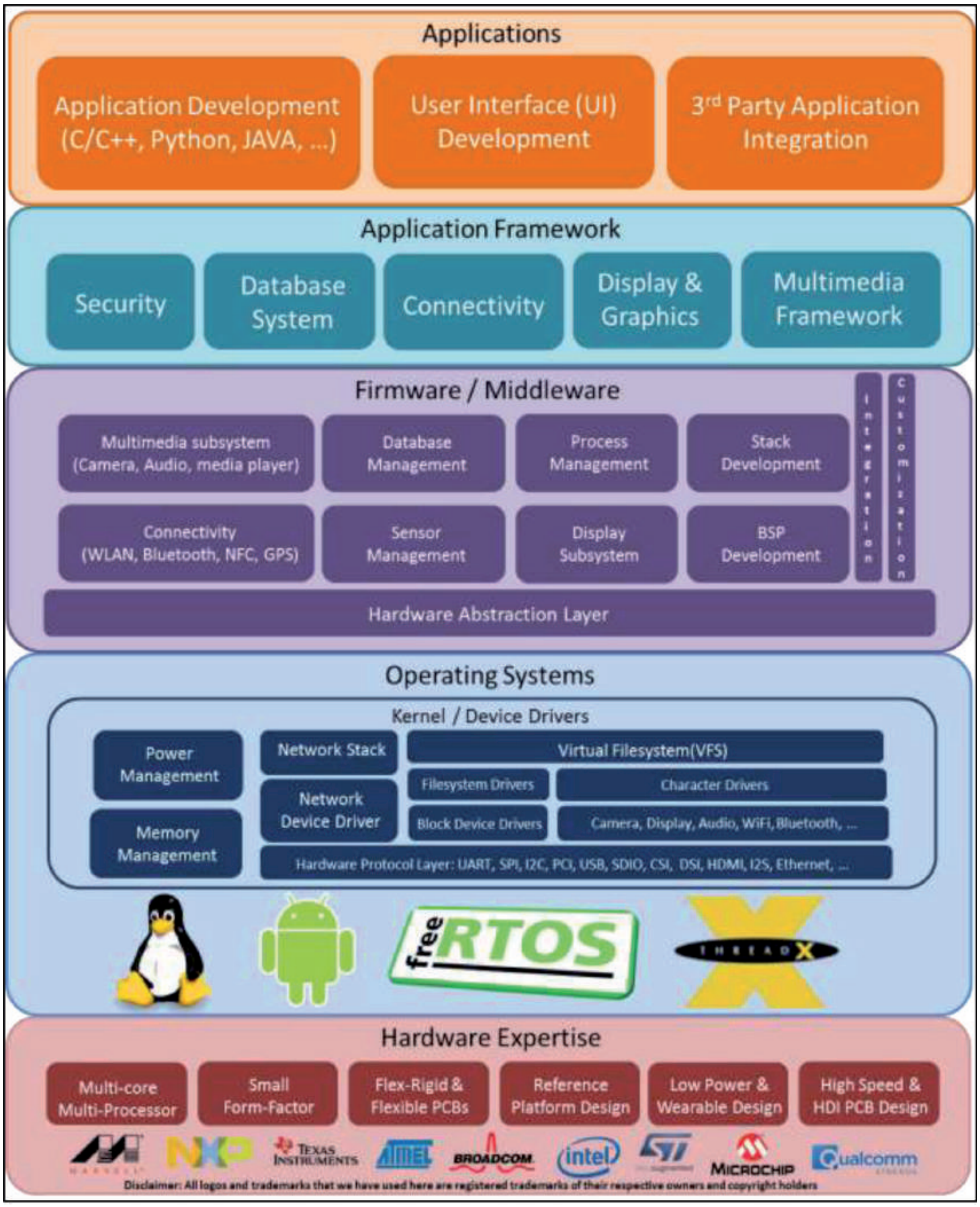

Figure 5.
Technology enablers (reference to https://volansys.com/product-engineering-services/).

technological enabler to the transformation of mass manufacturing into low-volume, high-mixed production. The discussion will focus on the product and system of edge computing and its underlying features as well as its association with manufacturing application and solution. As a reference, some of the tools used by Printed Power will be discussed.

4.1 Printed Power PowerEdge™

Printed Power has developed an IoT edge gateway product as shown in **Figure 6**, which is a powerful hardware platform with multiple protocol support for wired and wireless communication systems. Edge gateway product supports Android, Linux, and Ubuntu operating systems out of the box and can run a multitude of "apps" for each platform. It is a compact industrial PC combined with a powerful IoT gateway.

Figure 6.
Printed power PowerEdge™ hardware specification.

The PowerEdge™ product consists of RK3399 SOC, wireless radios, power modules, multiple GPIO and USB ports, and camera ports enclosed in a weather-proof enclosure with the following:

a. Light-weight operating system (OS): quick booting time and selected services running to reduce the dynamic memory consumption. The OS is based on the trimmed-down version of Android, Linux, or Ubuntu.

b. Embedded device driver development: able to support third party IoT devices interfaced over wired or wireless connectivity. Device drivers are dependent on the current OS running on the platform.

c. Embedded hardware development: able to install add-on hardware for the edge gateway to support IoT devices which operate at different power levels or nonstandard protocol.

d. OTA update support: allow updatable library packages inside the edge gateway for easier firmware upgrade which is completely wireless based.

On top of that, the Printed Power edge-cloud platform depicted in **Figure 7** allows the edge devices that are distributed throughout the factory shop floor and interconnected with the various machineries to gather at one place for monitoring and controlling. The cloud runs machine learning algorithm, makes java class image for download into the edge devices, and interoperates between the cyber cloud and the physical factory seamlessly.

4.2 Digital manufacturing application and solution

Let us first take a look at what a manufacturing production floor looks like and the kind of stuffs they do. A factory, manufacturing plant, or a production plant is an industrial site usually consisting of buildings and machinery, or more commonly a complex having several buildings, where workers manufacture goods or operate machines processing one product into another [4]. The area in a manufacturing facility is where the assembly or production is carried out either by an automated system or by workers or by a combination of both. The shop floor may include equipment, inventory, and storage areas. The basis of manufacturing [7] can be described in the following areas:

1. Assembly line: defines the progression and synchronization of work. The Ford example is typical of manufacturing, where there is a specific sequence of events which must be followed in order to produce the desired work product in a timely manner.

2. Division of labor: breaks the production process into separate tasks performed by specialists or craftsmen. Subdividing the process down into smaller increments provides the means to employ common workers as opposed to developing a dependence on highly skilled craftsmen which may add to the cost to the work product.

3. Precision tooling: provides mechanical leverage in the assembly line, the need for using the most technologically advanced tools, something that requires constant monitoring and upgrading.

Machines and the people are both working together in the shop floor and they operate with each other simultaneously. The machines are controlled by PLC logic and humans are controlled by themselves or by the company process. It is thus important that the two systems of their own talk with each other. **Figure 8(i)** is a snapshot of how this has being designed for an autonomous factory and it illustrates the architecture of such a platform design.

Referring to **Figure 8(ii)**, the robotic automation system of the autonomous factory consists of the arm performing pick and place, the moving robot to convey materials and products inside the factory, and the pressing and heating machine to treat and mold the made products. In order for the machines to communicate by themselves within the horizontal level of the manufacturing pyramid as discussed before, one has to first make a common communication language translator that allows cross talk among the machine systems. Printed Power PowerEdge™ fits in to provide the hardware connectivity as well as the firmware language translation.

Next, some form of intelligence is gathered from the data sets collected from the operations and maintenance to derive with the AI learning models for the control and automating of the manufacturing process. The AI learning is supported by both the online cloud-based engine as well as the offline edge Printed Power PowerEdge™ executable controls. GPU is part of this ball game to power up the AI engine and speed up the entire manufacturing process.

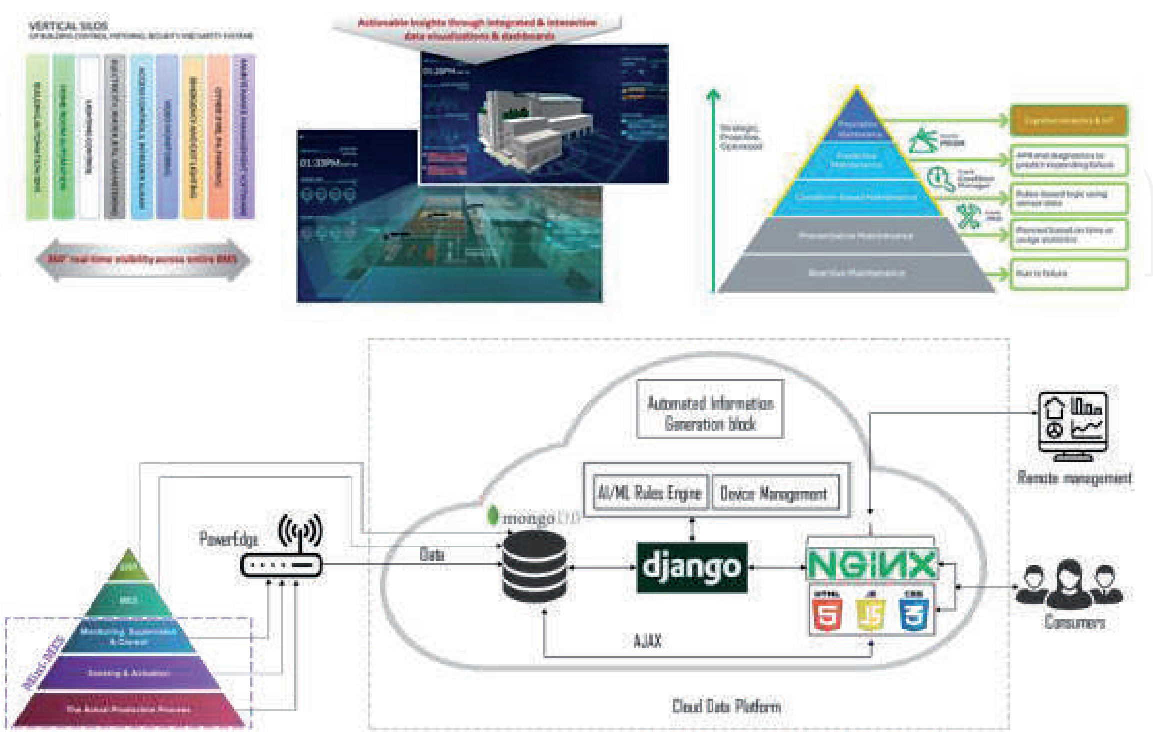

Figure 7.
Printed Power edge-cloud platform. (i) Description of platform components. (ii) Application of edge-cloud.

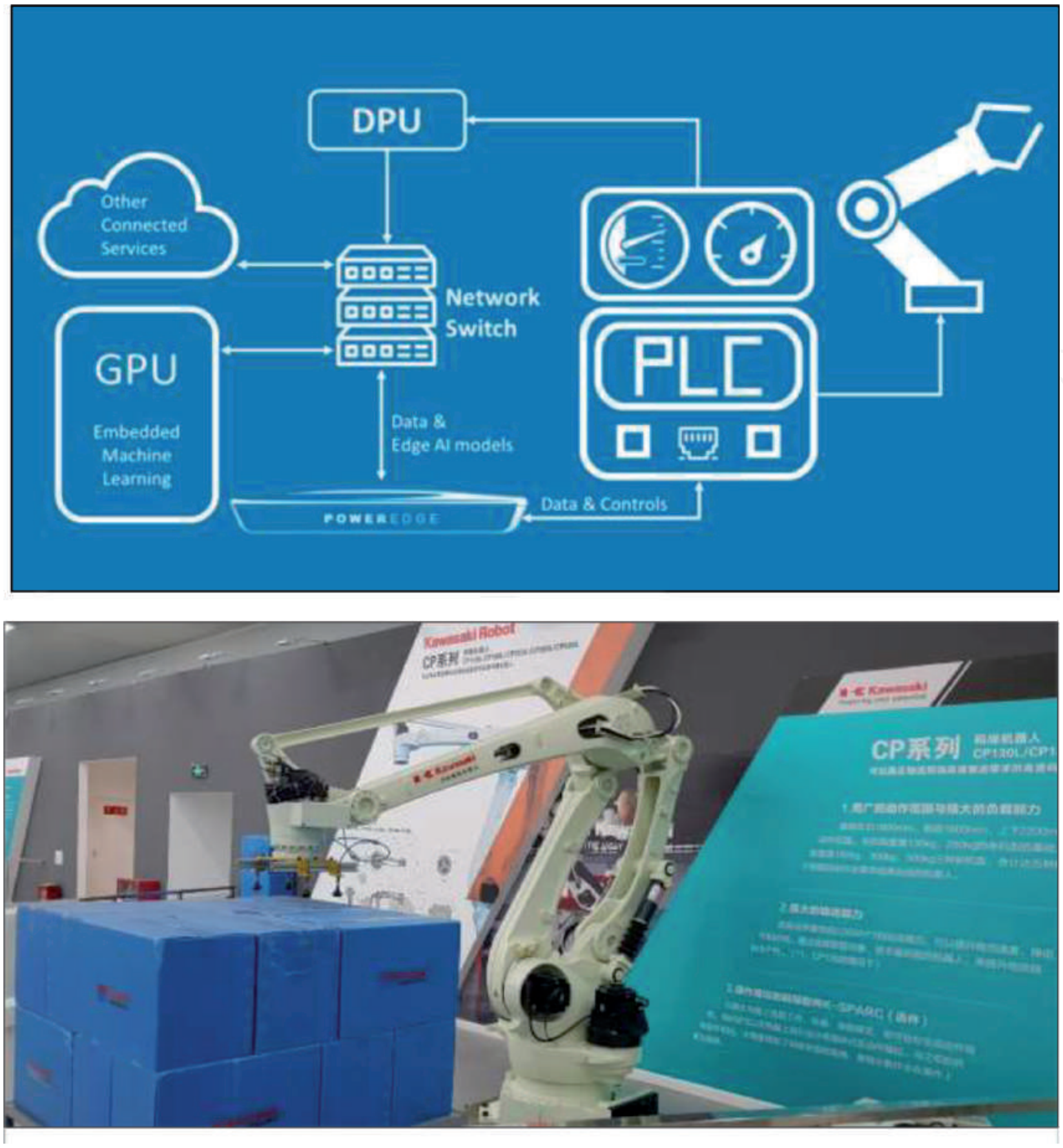

Figure 8.
Autonomous factory platform. (i) Printed Power digital manufacturing architecture. (ii) Robotic automation system.

Lastly, the remote manning and controlling of the entire autonomous factory platform is achieved via the dashboard at the command and control center. With the manufacturing and production status, the business owner is able to make a holistic and accurate decision with the sales figures, logistic and supply chain availability, demand and supply status, etc. Hence, this is a crucial part of the manufacturing application and solution.

The entire platform is undergoing development and installation at the site. It is expected to deliver its desired outcomes of being able to remotely access and control via the designed mini-MES platform with its backend housed on the AWS cloud. The autonomous factory should operate at its highest efficiency with the installed PowerEdge™ edge data compression for fast speed production and for onsite decision and execution for the real-time factory throughput.

5. Conclusion

Smart manufacturing initiative or movement from the industry transformation perspective is rapidly emerging in many parts of the world. Today, mass production is making things (products and systems) in a gigantic way that everyone is consuming them not at their preferences. The made from the "one mold fits all" approach does not seem to work for the consumers. The new world of making things is going to be so agile, so optimized and integrated, and so fast in speed and precise in accuracy to benefit and satisfy the fast consuming and highly personalized needs of the people.

To address this, the chapter discusses the digital manufacturing technology made by a Singaporean company, Printed Power, for the plant to be remotely manned and controlled by a press of a button. This autonomous factory software platform which is being developed allows for: (1) the remote connectivity for the manufacturing solution to access their local factory floor within China and (2) the 24 × 7 real-time outside China monitoring and managing of the factory production system.

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Chapter

Optimization of Manufacturing Production and Process

YinQuan Yu

Abstract

This chapter mainly introduces production processing optimization, especially for machining processing optimization on CNC. The sensor collects the original vibration data in time domain and converts them to the main feature vector using signal processing technologies, such as fast Fourier transform (FFT), short-time Fourier transform (STFT), and wavelet packet in the 5G AI edge computing. Subsequently, the main feature will be sent for cloud computing using genetic programming, Space Vector Machine (SVM), etc. to obtain optimization results. The optimization parameters in this work include machining spindle rotation velocity, cutting speed, and cutting depth, while, the result is the optimized main spindle rotation speed range of CNC, which met machining roughness requirements. Finally, the relationship between vibration velocity and machining quality is further studied to optimize the three operational parameters.

Keywords: machining processing optimization, time domain, short time Fourier transform, wavelet packet, genetic programming, deep learning

1. Introduction

The International Federation of Information Processing (IFIP) defines a numerically controlled (also commonly called **CNC**) machine tool as a machine tool equipped with program control. The difference between CNC machine tools and ordinary machine tools lies in the working sequence of NC machine tools: according to the requirements of part processing, CNC language is used to write processing sequences and parameter programs. After the program is analyzed and processed by the CNC device, the execution instructions are sent to the servo system to actuate the motion of the machine tool [1]. Programming controlled movement of the main spindle and worktable completes the processing that does not exist in ordinary machine tools. As shown in **Figure 1**, the mechanical aspects of CNC machine tools mainly include three major parts: the main shaft component [2], followed by the support component, and the conveying mechanism [3]. The main shaft is partially driven by a high-precision stepper motor or servo motor instead of a conventional motor. The transmission part uses a ball lead screw with less resistance and greater rigidity without backlash instead of the traditional lead screw. The CNC system controls the movement of the mechanical structure of the CNC machine tool to complete the processing of parts. The main component is the MCU. The coordination between its functions is an important index for evaluating the CNC machine tool and the CNC system [4].

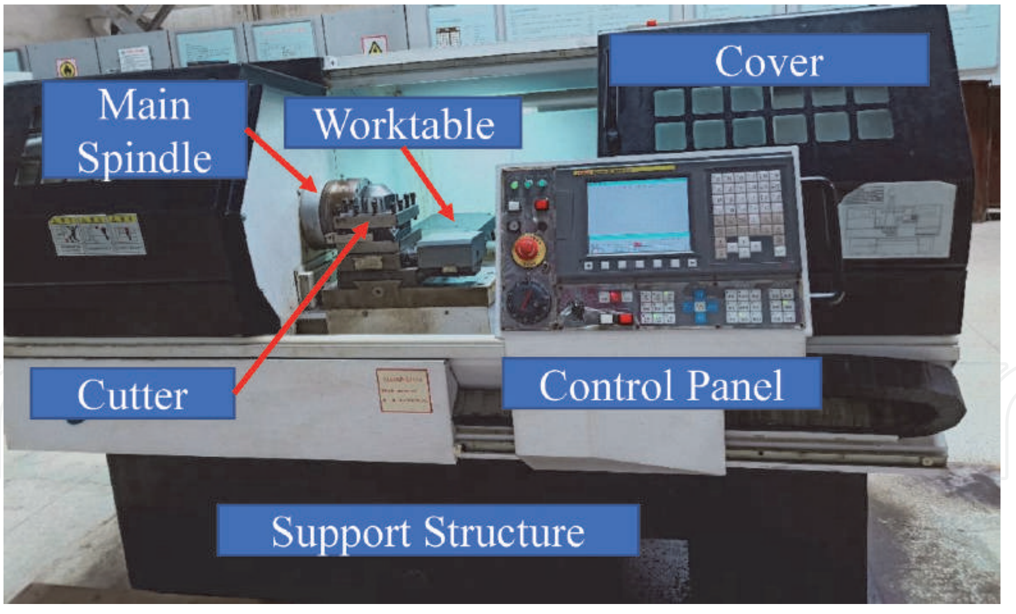

Figure 1.
Components of a CNC lathe.

The optimization of CNC machine tools mainly includes the following three aspects:

1.1 Mechanism optimization

Improving machining accuracy of the machine tool must start from the design stage of the NC machine tool, adopt the drive device with outstanding dynamic performance, and use advanced control technology to improve anti-interference ability of the servo system [5–9]. Structural optimization design can calculate the durability and maintainability of NC machine tools, and design reliability by calculating the space error model of XYZ CNC machine tools by first-order and second-order matrices, Monte Carlo method, etc. [10]. By studying the kinematic configuration of CNC machine tools, it is found that it directly affects the nonlinear errors generated in the process of free-form surface machining [11], and has a direct impact on processing energy consumption and design of the supporting CNC system [12]. The moving parts of CNC machine tools and the mechanism of each feed axis also have a significant impact on the overall rigidity [13], positioning error [14], maintainability [15], and other indicators of CNC machine tools, which determine machining accuracy and work reliability [16]. The spindle of CNC machine tools can be analyzed and optimized by finite element analysis [17]. The finite element modeling can appropriately simplify some chamfers, small holes, etc. that do not affect mechanical properties [18]. The denser and more accurate the finite element (FEM) mesh division, the longer the optimization calculation time [19]. The method of selecting the appropriate unit division, which is not discussed here, can be found in ANASYS-related books. In addition to the influence of the spindle of the CNC machine tool, the deformation of the CNC machine tool due to insufficient static stiffness [20] causes deviations between the actual position and the ideal position of the tool and the workpiece, and seriously affects its machining accuracy. The guide rail has a decisive influence on the accuracy of the machine tool [21]. The optimized design of the guide rail of the machine tool can significantly improve the geometric accuracy of the bed rail, thereby significantly enhancing the machining accuracy of the NC machine tool. Furthermore, selecting the right load rail by speed can optimize the machining quality. In terms of precision machining, a reasonable milling process should be selected according to different materials [22]. Choosing a suitable processing tool and enhancing the strength of the processing tool can avoid vibration caused by the high speed of the machine tool spindle during processing, which will affect processing accuracy [23]. For example, in the process of boring bar technology processing, strong heat treatment technology can be used to improve the rigidity and strength of its material. The error of the tool during manufacturing and machining wear [24] requires us to monitor it in real time to detect problems in time, check and integrate and summarize these problems, and then establish an error compensation model through the data system [25]. The influence of tools and bearings on the accuracy of machine tools is obvious [26]. The machining process should select the tool based on the cutting degree, depth, and accuracy of the parts [27], and the bearing selection should use bearings with relatively low friction resistance and high degree of smoothness and stability. During gear machining, the accuracy of the machine tool will affect transmission characteristics during gear machining [28–30]. The machining process can be regarded as the cutter wheel axis revolving around the center axis of the production wheel. Cogging is processed by 3–7 groups of tools. After each cogging is processed, the workpiece rotates and the next cogging is processed. Cutting tools installed on the tool turret includes outer blade, middle-outer blade, middle-inner blade and inner blade. There are three main methods to check the machining accuracy of CNC machine tools [31]: sample detection method, indirect detection method [32], and direct detection method.

1.2 Energy consumption optimization

The energy-saving process optimization of CNC machine tools usually divides the machine tool's energy consumption into several parts [33]; the auxiliary system, the main drive system, the feed system, and the process of cutting and load. Gaussian process regression models are established according to these five parts, and the differential evolution algorithm is used to optimize the model. According to the processing requirements, a model of the energy consumption, cost, and time of the cutting process is established. The dynamic multi-swarm particle swarm optimization algorithm is used for calculation to obtain more diverse and convergent results [34]. The energy consumption of CNC milling machines can be divided into three parts, namely fixed energy consumption, no-load energy consumption, and milling energy consumption [35]. It can analyze the multi-source energy flow of the machine tool and the energy consumption of the machining process to establish the power of the machining stage equations and energy consumption estimation models. The calculation of energy consumption can be carried out from the amount of cutting, processed gears, cutting tools, cutting fluids of CNC machine tools, etc. to study carbon emissions [36]. The finished processing time is then established. The machining surface accuracy and other conditions are based on the reduction of carbon emissions from the spindle speed and feed rate during machining. A multi-objective optimization model for optimizing carbon emissions and processing costs can be established [37], which can be solved by genetic algorithms [38], and the feasibility of the optimization method of the model is verified by simulation calculation. On the digital intelligent machine tool, a system for detecting the energy consumption of the machining process of the CNC machine can be designed based on the upper computer information interaction unit and the lower computer information acquisition element.

1.3 Process optimization

The process design optimization of CNC machine tools has a significant impact on their precision performance. The design of the machining process of the machine tool should determine the processing steps and clamping methods of the workpiece by analyzing the mechanical drawings of the parts; the geometric elements of the outline of the part, the accuracy requirements of the dimensional tolerances, the accuracy requirements of the shape and position tolerances, surface smoothness requirements, material quality requirements, and the number of processes mode [33]. The feed route, choice of cutting amount, and choice of tool can then be determined. In order to prevent the tool from colliding with the workpiece during the machining process, the optimization of the machining process must be carried out by interference avoidance research [39, 40]. Based on the algorithm of coordinate extremes, the complex surface should be simplified by taking an arc of the surface [41], and performing measurement on the bisector. The vibration of the machine tool gravely affects its machining accuracy [42]. The hardness and thickness of the workpiece during the machining process [43] and the force of the machine tool are taken into consideration [44]. For the movement path [45], the movement speed [46] is optimized to achieve the machine vibration damping control. Another vibration reduction method is passive vibration reduction, which using materials with strong vibration resistance strengthens the stability of CNC machine tools [47]. Another factor affecting the machining accuracy of CNC machine tools is thermal deformation. During the working process of the machine tool, the moving parts of the machine tool will be affected by thermal deformation, which will cause relative displacement between the tool and the workpiece [48]. The solution is to strengthen cooling and lubrication during the work process to reduce the displacement [49]. The thermal characteristics, machining environment, and specific cutting parameters of the machine tool determine the size of the thermal error by solving the function of the time-varying temperature field under given conditions [50]. The purpose of the auxiliary heat source is to balance the temperature field to reduce heat source interference. In short, the errors caused by structural deformation, vibration, and high temperature in CNC machine tools can be compensated with the following methods: single error synthesis compensation technology [51], geometric error direct compensation technology, geometric error synthesis compensation technology [14], single-term error synthesis compensation technology by studying the error produced by a certain CNC machine tool, and geometric error direct compensation technology by measuring the error data to directly error compensation on the CNC machine tools. Using geometry error synthesis compensation technology, the unidirectional error information is decomposed by obtaining the synthetic error value of the CNC machine tool. It is particularly important to emphasize the tremendous difficulty in accurately measuring the angular error of the spindle during the general process; however, it can now be solved by a matrix using a laser interferometer [52]. For complex curved surface processing, multi-step compensation must be adopted as follows: (1) pre-compensation; (2) error detection; and (3) reverse compensation. For the deformation of the tool during machining, mirror image anti-deformation compensation that mirrors the tool position point and the tool axis vector must be adopted [53].

To sum up, the reliability of CNC machine tools is guaranteed by the processing quality of each part of the CNC machine tools, and the quality of processed parts is controlled by the quality of the processing procedures. For the analysis of the machining process of the machine tool, it is necessary to analyze the machining process of a key part. The optimization parameters of CNC machine tool machining process are mainly energy consumption during machining, machining efficiency, and machining accuracy. Due to the limited space, this chapter only discusses the influence of optimization parameters on machining accuracy.

2. CNC common processing optimization approach

The Computer Numerical Control (CNC) machine tools lie in the working principle of CNC machine tools: according to the requirements of part processing and using CNC language, the processing sequence is written into parameter programs, and the program is analyzed by Multipoint Control Unit (MCU). After processing, the execution instructions are sent to the Driving System of step motors or Servo motors and the machine tool will start machining the work piece. The position and velocity signals of the machine tool will then be sent back to the MCU. The schematic of CNC is shown in **Figure 2**.

From a mechanical point of view, CNC machine includes three main sub-systems: the main spindle sub-system, followed by the supporting sub-system and the conveying mechanism sub-system. From a control point of view, it mainly includes two sub-systems: Data Processing Unit and Control Loop Unit. The processing of parts action is completed through the numerical control system by controlling the mechanical structure of the CNC machine tool. The coordination between their functions is an important index for evaluating the machine tools under the CNC system. To fully utilize the merits of CNC for precision machining, a reasonable milling process should be selected according to different materials. Vibration caused by excessive rotation speed of the machine tool spindle will affect machining accuracy. The outer ring can be processed after specific processing. During the process of boring bar technology, thermal stiffness enhancement technology can be used to improve the rigidity and strength of the material.

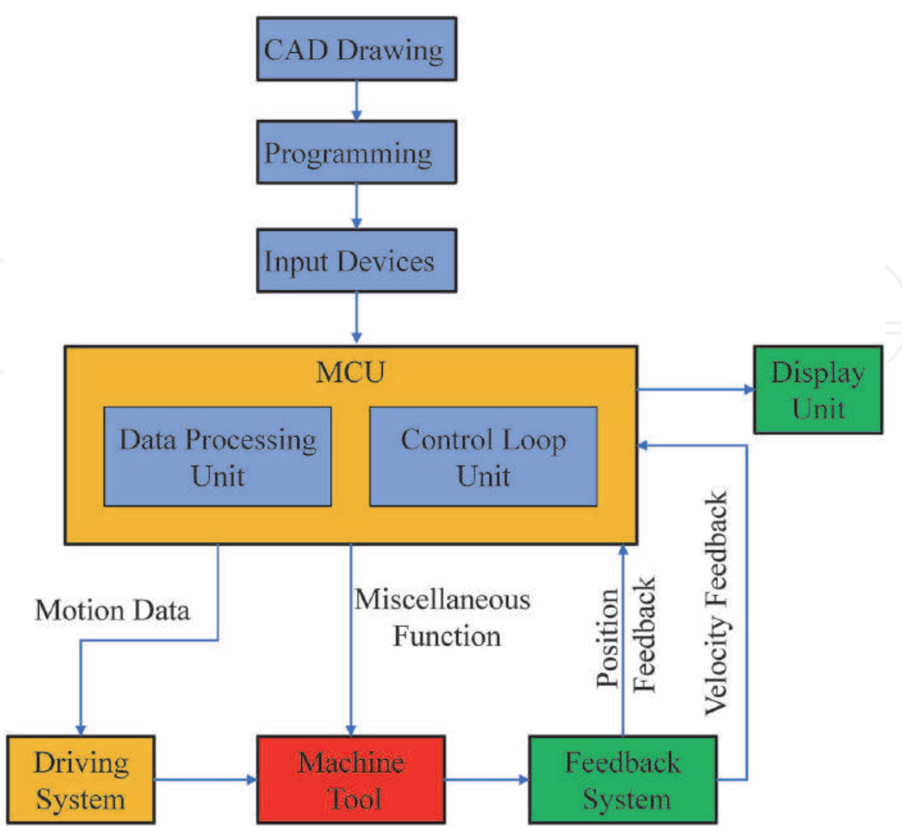

Figure 2.
Schematic diagram of CNC.

2.1 Cutting force monitoring

To obtain the wear and tear errors in the manufacturing and processing of cutting tools, we need to monitor them in real time to detect problems in time, check, integrate, and summarize them, and then establish them through the data system error compensation model. The deformation of the machine tool due to insufficient static stiffness, which causes deviations between the actual position and the ideal position of the tool and the workpiece, seriously affects its machining accuracy. In Precision Machining process on CNC, the cutting force in tangential and radial directions needs to be predicted based on monitoring signals and machining process parameters such as cutting depth, cutting width, rotational speed of the main spindle, and feed speed of the cutting tool. The experimental data of the cutting forces are shown in **Figure 3**.

2.2 Processing path optimization

The kinematic configuration of CNC machine tools directly affects the nonlinear errors generated in the process of free-form surface machining, and has a direct impact on processing energy consumption and design of the supporting CNC system.

After determining the motion configuration of the CNC machine tool, the mechanism of each feed axis has a significant impact on the overall rigidity, positioning error, maintainability, and other indicators of the CNC machine tool, which determine its machining accuracy and work reliability. For instance, in order to machine complex surface S12, it needs to be decoupled into surface S1 and S2. According to the required feed motion of surface S1 and S2, we can get the feed motion of combined curved surface S12 as shown in **Figure 4**.

A heuristic algorithm (HA) is one that is designed to solve a problem in a faster and more efficient fashion than traditional methods at the expense of optimality, accuracy, precision, or completeness. Although it has the capability of convergence and obtaining the optimization result efficiently, it depends heavily on initial result and may only obtain local optimal solution of non-smooth curve functions. Moreover, it occupies a large amount of computing resources and has a poor real-time performance, which may be incompatible with Computer Aided Manufacturing (CAM) on CNC. In order to overcome this issue, a discrete tool planning is proposed as follows:

$$Path = \left\{(A,C)^{1}_{path_1}, (A,C)^{2}_{path_2}, (A,C)^{3}_{path_3}, \ldots (A,C)^{m}_{path_m}\right\}. \tag{1}$$

where, $(A,C)^{m}_{path_m}$ represents the positions of two rotary feed axes A and C when the cutting point is on m.

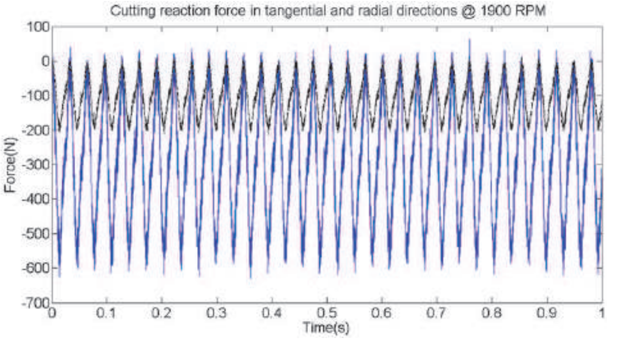

Figure 3.
The experimental cutting forces in tangential and radial directions.

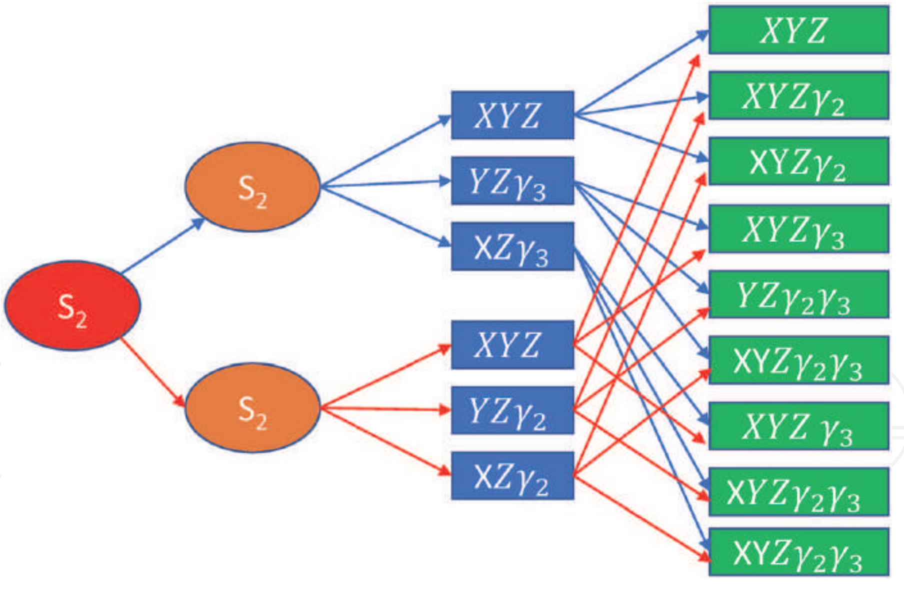

Figure 4.
The feed motion of S12 obtained from that of decoupled surface S1 and S2.

One methodology for positioning error compensation of CNC machine tools is through interpolation. It produces third-order splines from the coordinates of discrete points measured by Laser Doppler velocimetry (LDV). Between $[x_i{-}1, x_i]$, the interpolation function of splines $s(x)$ can be deduced as

$$s(x) = \frac{\left[(x_i - x)^3 * M_{i-1} + (x - x_{i-1})^3 * M_i\right]}{6h_i} + \left(y_{i-1} - \frac{h_i^2}{6} * M_{i-1}\right)\frac{x_i - x}{h_i} + \left(y_i - \frac{h_i^2}{6} * M_i\right)\frac{x - x_{i-1}}{h_i}, \text{i} = 1, 2, \ldots \text{n} \tag{2}$$

In order to obtain M_{i-1}, let

$$\begin{cases} d_i = \dfrac{6}{h_i + h_{i+1}}\left(\dfrac{y_{i+1} + y_i}{h_{i+1}} - \dfrac{y_i + y_{i-1}}{h_i}\right) = 6f(x_{i-1}, x_i, x_{i+1}) \\ u_i = \dfrac{h_i}{h_i + h_{i+1}}, \lambda_i = \dfrac{h_{i+1}}{h_i + h_{i+1}} = 1 - u_i \end{cases} \tag{3}$$

Since the binomial multi-order derivative is continuous, M_i satisfies N − 1 equations,

$$u_i M_{i-1} + 2M_i + \lambda_i M_{i+1} = d_i \; i = 1, 2, 3 \ldots, n - 1 \tag{4}$$

The first type of boundary conditions is

$$S'(X_0) = f_0' = m_0, S'(X_n) = f_n' = m_n \tag{5}$$

Then, Eq. (4) can be present as

$$\begin{bmatrix} 2 & \lambda_0 & & & \\ \mu_1 & 2 & \lambda_1 & & \\ & \cdots & \cdots & \cdots & \\ & & \mu_{n-1} & 2 & \lambda_{n-1} \\ & & & \mu_n & 2 \end{bmatrix} \begin{bmatrix} M_0 \\ M_1 \\ \cdots \\ M_{n-1} \\ M_n \end{bmatrix} = \begin{bmatrix} d_0 \\ d_1 \\ \cdots \\ d_{n-1} \\ d_n \end{bmatrix} \tag{6}$$

2.3 Processing dynamic profile optimization

To prevent CNC machining in normal condition, the acceleration and velocity of the moving stages have to be monitored and should be less than the maximum design range of CNC machine.

With the known coordinates of two adjacent track points (x_{n+1}, z_{n+1}), (x_n, z_n) and the velocity of the main spindle, the acceleration and velocity of point n are approximately.

$$\Delta t = \frac{\Delta\theta}{\omega}, v_n = \begin{bmatrix} \dfrac{x_{n+1} - x_n}{\Delta t} \\ \dfrac{z_{n+1} - z_n}{\Delta t} \end{bmatrix}, a_n = \begin{bmatrix} \dfrac{\dot{x}_{n+1} - \dot{x}_n}{\Delta t} \\ \dfrac{\dot{z}_{n+1} - \dot{z}_n}{\Delta t} \end{bmatrix}. \tag{7}$$

Figure 5 shows the monitored acceleration in x and z directions respectively. Their values should be within CNC machine design range. NC machining process usually faces "over cutting" issue, which can be minimized through the commonly used method of rotating the tool angle as shown in **Figure 6**.

The extreme value $S_t$and root mean square value S_q of the machining surface shape are the two major indicators of the machining accuracy and are calculated by the following equations:

$$S_t = \max(e) - \min(e), S_q = \sqrt{\sum_{i=1}^{n} e_i^2 / n}. \tag{8}$$

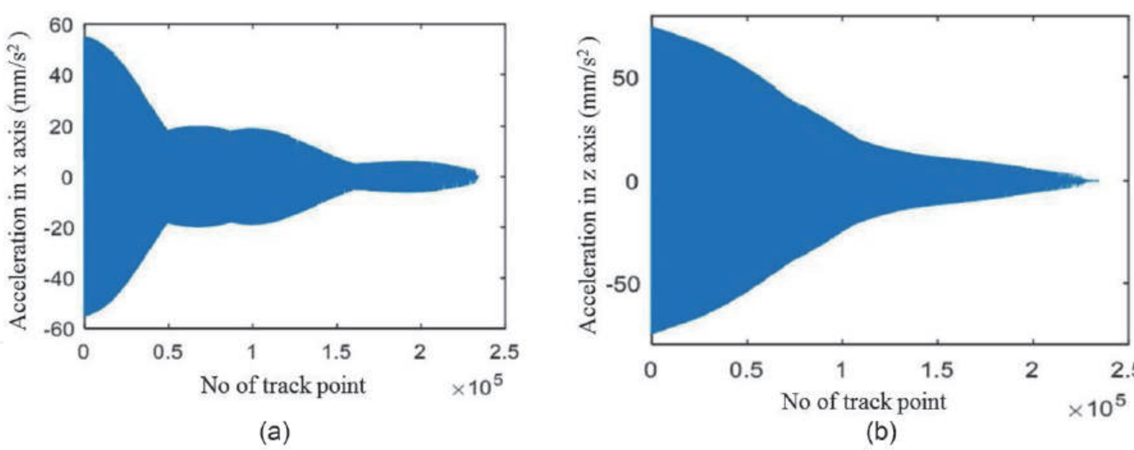

Figure 5.
Discrete point acceleration of machining trajectory. (a) Acceleration of track pint in x axis and (b) acceleration of track pint in x axis.

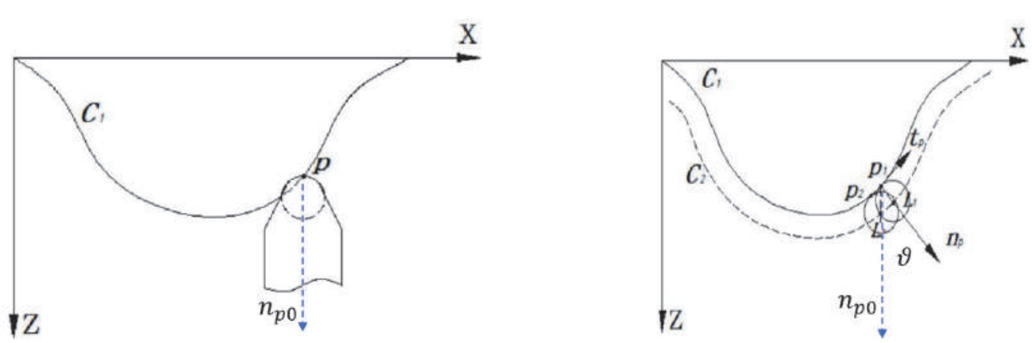

Figure 6.
Machining tool overcutting compensation.

where e represents the shape tolerance of the machining surface, N represents the number of the measured point.

Figure 7 shows the implementation of cutting tool compensation to reduce the machining error. It can be seen that tool compensation can effectively solve machining errors from 0.8 to 0.5 μm due to overcutting of tools through rotating cutting tool angle ϑ.

To minimize the value of S_(t)and S_(q), the optimized machining profile should be conducted as shown in **Figure 8**. In order to make the movement of the machine tool smooth and the processing more stable, the concept of "jerk" is introduced and made as constant. Then, the profile of acceleration is trapezoid. It can be seen that the speed profile of trapezoid acceleration is smoother than that of constant acceleration. As we know that the reaction force of the worktable and feed screw becomes infinite if the acceleration is suddenly changed. As a result, it may damage some motion transmission parts of CNC, such as worktable, lead screw, or servo motor.

Usually, in order to obtain high quality of the machining parts and extend the working life of the CNC machining, the speed of CNC is kept as constant as possible besides start and end stage of the machining processing.

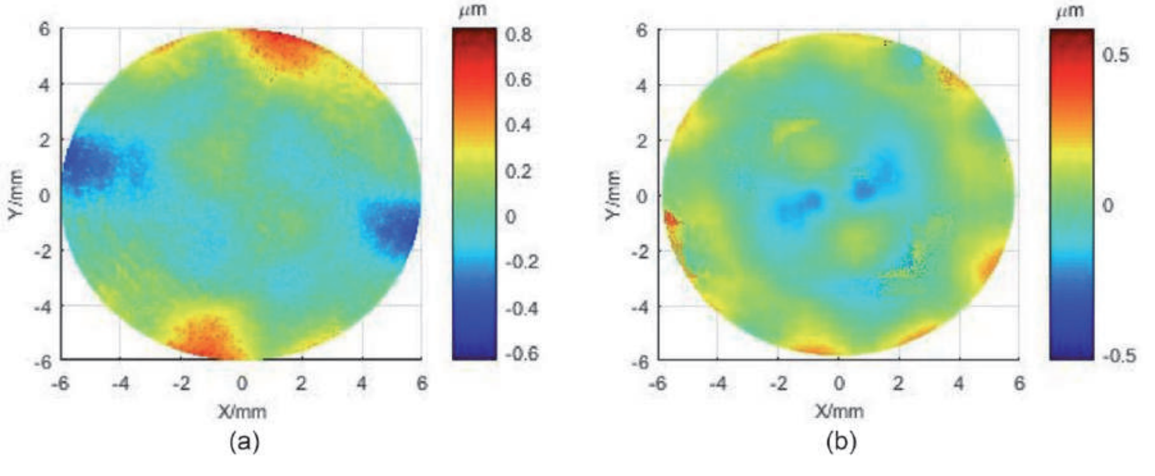

Figure 7.
Cutting tool compensation to reduce machining error. (a) Machining error before tool compensation and (b) machining error after tool compensation.

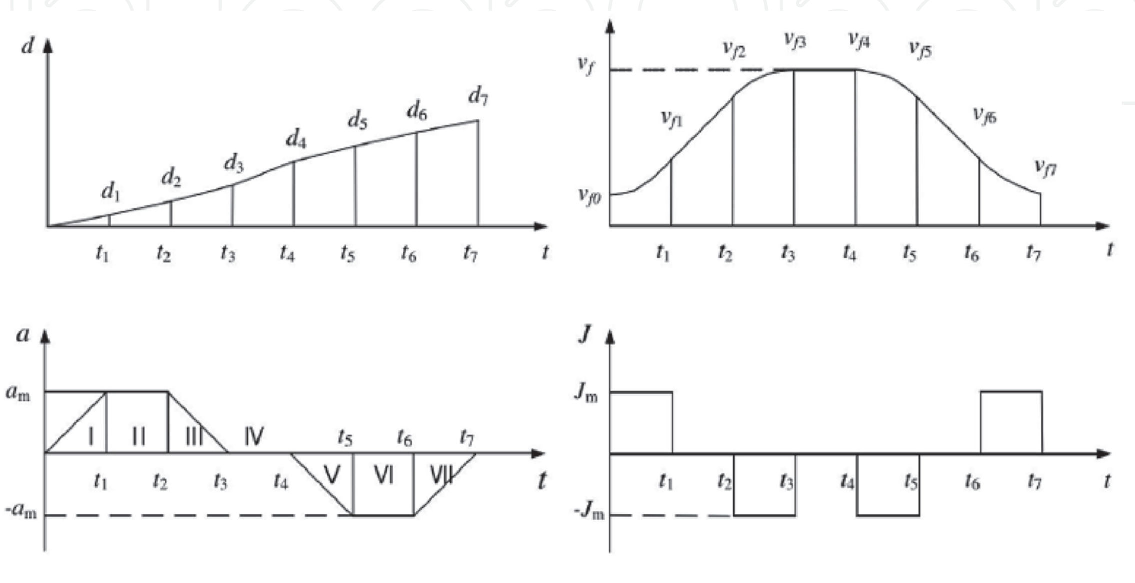

Figure 8.
Distance, velocity, acceleration, jerk vs. time profile in acc/dec process of CNC machining.

3. Processing tools deflection compensation

Any machining process will induce dynamic reaction forces on the cutting tool. Cutting tool deflection due to improper clamping, tool wear, and error in machine accuracy may lead to error in the final product. Hence, the current trend in the industry is to detect such errors and compensate for them in machining to avoid scraping the material afterward. In this chapter, we attempt to detect the cutting tool deflection while machining the workpiece and hence predict error on the workpiece. To detect the deflection during machining, we use either a contact or a non-contact sensor. One of the major considerations in choosing the right sensor is cost and ability to measure the error under harsh environments. In this section, compared to capacitive probe, we finally decide to adopt eddy current gap sensors to detect deflection of the cutting tool during machining of a simple profile and predict error on the workpiece. The predicted error was then verified using Coordinate Measuring Machine.

3.1 Displacement sensor for tool compensation

To compensate for the cutting tools or work piece deflection, there are two types of commonly used displacement sensors to monitor: (1) capacitance gap sensors and (2) Eddy current type gap sensors.

3.1.1 Capacitance gap sensors

The capacitance of a parallel-plate capacitor is given by

$$C = \frac{\varepsilon_r \varepsilon_0 A}{d} \tag{9}$$

where, ε_r represents electric constant of the insulating medium ($\varepsilon_r = 1$ for air); ε_0 represents permittivity of air or vacuum, which is 8.85×10^{-12} F/m; A represents overlapping area in plates; and d represents varying distance between the bottom surface of the electrode of capacitive probe and the surface of measured object (tool cutting tip).

The working schematic of the capacitive probe is shown in **Figure 9(a)**. It is evident that changes in the distance between the capacitive probe and the measured object (cutting tools) change the capacitance, which in turn changes the current flow in the sensing element. RF oscillator generates 500 kHz and 1 MHz high-frequency electric field to focus the sensing field on the cutting tool. **Figure 9(b)** shows the relationship between distance d and capacitance c. It shows d decreases as c increases. Based on this principle, the distance between plates can be determined by calculating the capacitance value.

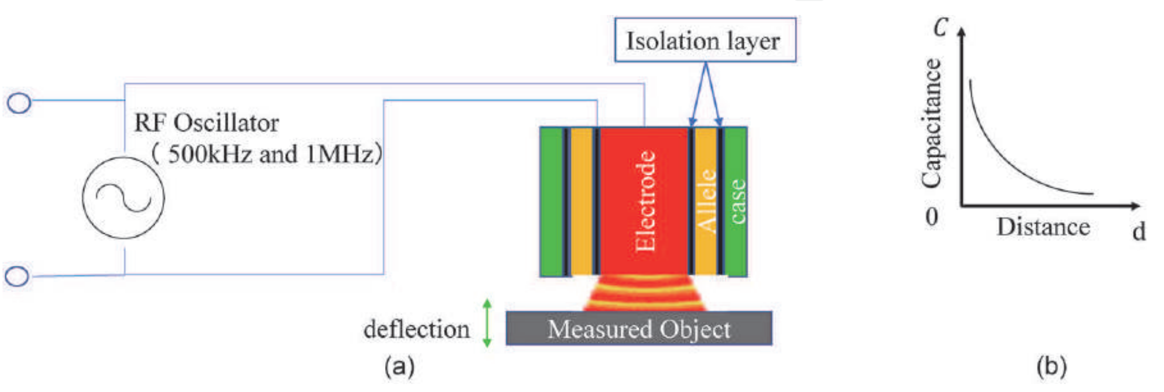

Figure 9.
The working schematic and principles of capacitive probe. (a) Schematic of capacitive probe and (b) capacitance vs. distance.

3.1.2 Eddy current type gap sensors

The working schematic of eddy current gap sensor is shown in **Figure 10**. When a nonmagnetic conductive target material is introduced into the coil field, eddy currents are induced on the target's surface. These currents generate a secondary magnetic field, inducing a secondary voltage in the sensor coil. The result is a decrease in the coil's inductive reactance (the coil-target interaction is similar to the field interaction between the windings of a transformer). By calculating the "effective impedance" of the sensor coil, the distance to the target can be determined.

Nonmagnetic conductive target materials (e.g., aluminum, copper, brass, gold), with low resistivity and a magnetic permeability of 1, can provide output sensitivity in terms of impedance change per unit of target displacement.

The capacitive probe is suitable for measuring any metal surface. Its measuring accuracy can reach up to several nanometers. However, the dusty working environment is not suitable for applying capacitive probe to measure the target, as the gap between probe and the measured target is contaminated by dust, liquids such as coolant. As a result, the measuring accuracy of the capacitive probe is affected. On the other hand, the current gap sensor is suitable for measuring conductive material except steel. However, it cannot measure thin materials because of insufficient eddy current generated, thus affecting the measuring accuracy of the gap sensor.

3.2 Tool deflection compensation approach

Figure 11 shows 5G AI Edge computing configuration for CNC cutting tool deflection compensation. The original signal is collected by sensor and sent to 5G AI computing for preprocessing such as noise reduction with low-pass filter, compressed data etc. The dimension-reduced data is sent for cloud computing through a 5G network router. The cloud computing device uses genetic programming (refer to **Figure 12**) to generate the cutting tool deflection compensation algorithm and sends it back to the 5G AI edge computing local network. 5G AI edge computing device then calculates the compensation value and sends it to MCU to compensate for the cutting tool deflection.

3.3 Algorithm adopted in tool deflection compensation

Genetic programming (GP) is adopted in this study to conduct tool deflection compensation. It evolves from computer programs that are traditionally represented in memory as tree structures. Trees can be easily evaluated in a recursive manner. Every tree node has an operator function and every terminal node has an operand, rendering mathematical expressions easy to evolve and evaluate. Thus, traditionally GP favors the use of programming languages that naturally embody tree structures.

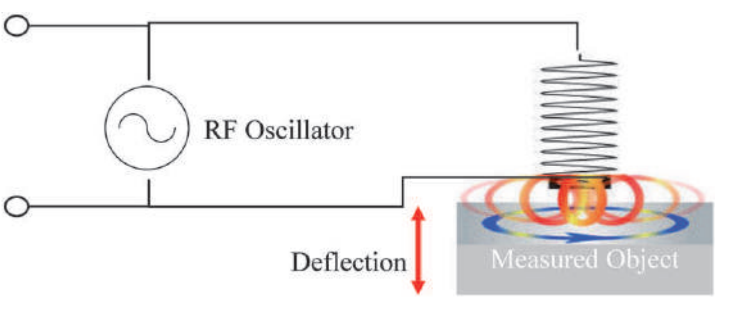

Figure 10.
The working schematic of eddy current gap sensor.

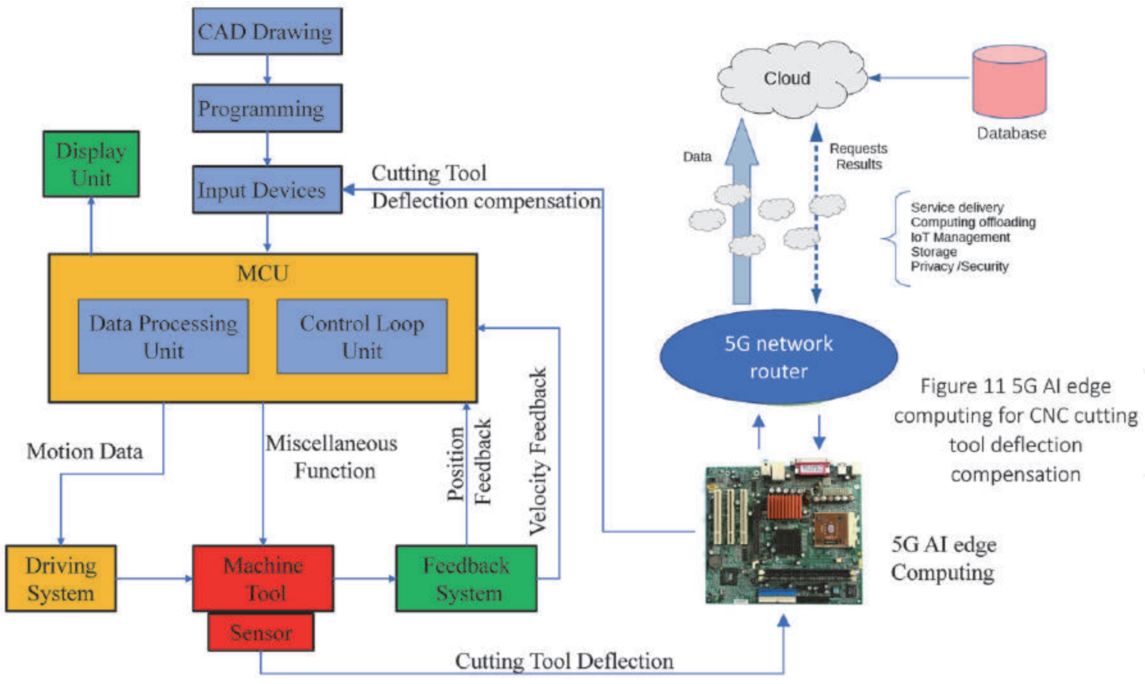

Figure 11.
5G AI edge computing for CNC cutting tool deflection compensation.

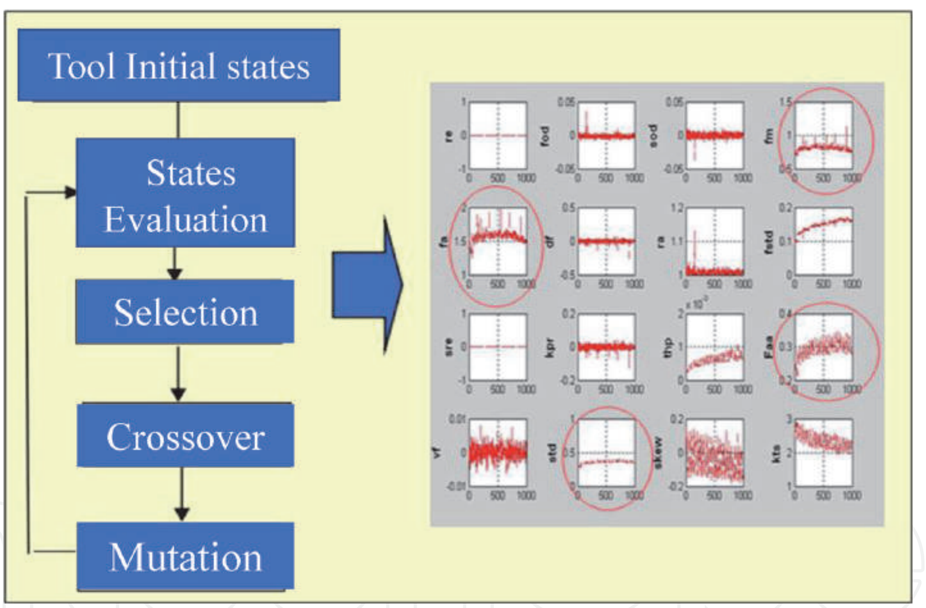

Figure 12.
Schematic of genetic programming for tool deflection compensation.

GPLAB is a genetic programming toolbox for MATLAB® initially developed by Sara Silva. The main modules of GBLAB are GENPOP, GENERATION, and SETVARS. GENPOP module generates the initial population and calculates its fitness based on default or user defined fitness function. Terminal set:

Terminal set: "X1," "rand," and "100".

Terminal condition: Maximum generation reached.

Function set: plus (+), minus (−), times (*) and other protected function in.

Fitness function: Fitness function is defined as the minimum value between actual value and predicted value. During the programming calculation process, the new population should be superior to the previous population. In other words, the new fitness value will be lower than previous one.

$$\text{Fitness} = \min \ (\text{abs}\,(\text{predicted result} - \text{expected result})). \tag{10}$$

The schematic of genetic programming for tool deflection compensation is shown in **Figure 12**. The optimal tool deflection compensation algorithm is obtained through hundreds of generation selection, crossover, and mutation operation until set fitness function is reached.

3.4 Tool deflection compensation experiment

The material of cutting tools includes high-speed steel, ELMAX chromium-molybdenum-vanadium alloy steel, or nickel-chromium alloy steel. However, the cutting chip will reduce the capacitive probe measurement sensitivity and accuracy and damage the capacitive probe. Therefore, the eddy current gap sensor will be adopted in this working environment. The deflection signal is sent to 5G AI edge computing for signal pre-processing, before sending for computing through genetic programming. The computing results are sent back to MCU of the CNC to control the movement of the main spindle and the worktable.

The cutting surface error compensation with and without cutting tool deflection compensation are shown in **Figure 13**. It shows that the maximum machining error

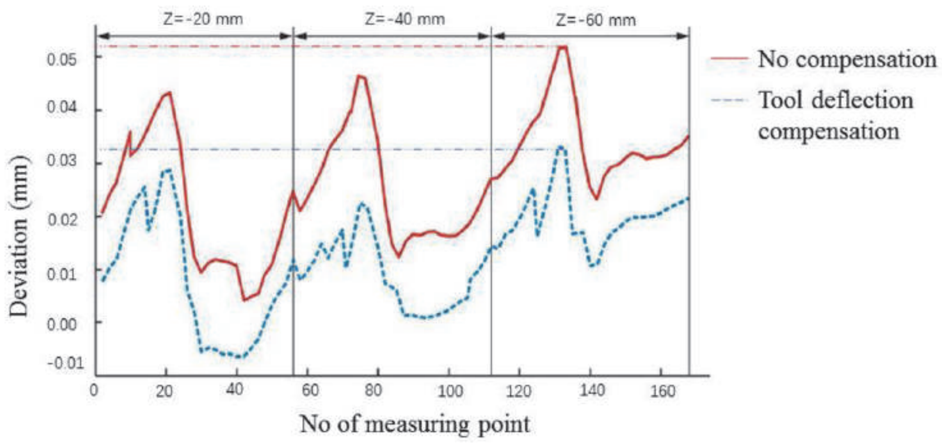

Figure 13.
Cutting surface error with/without tool deflection compensation.

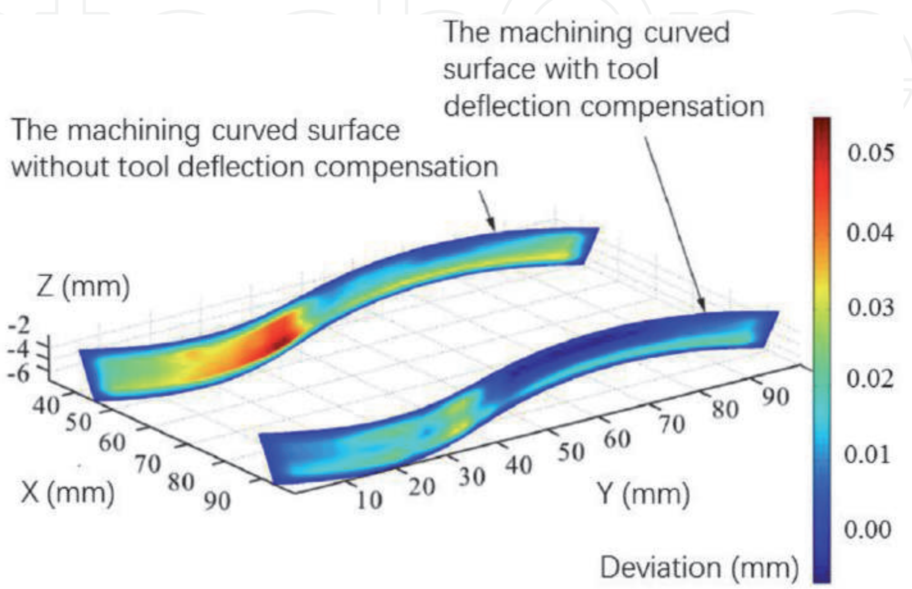

Figure 14.
The deviation distribution of the machining with/without tool deflection compensation.

is reduced from 0.053 to 0.032 mm, which is 40%. The deviation distribution of machining with/without tool deflection compensation is shown in **Figure 14** in three dimensions. It can be seen that at almost all measured points, the machine error on a curved surface without tool deflection is larger than that on a machining curved surface with tool deflection compensation. Moreover, the error is largest at the bottom area of inflection of the curved surface, reaching 0.053 mm. This may be due to two reasons. First, the cutting tool suffered the largest reaction force and induced the largest deflection. Second, the stiffness of the machining tool is smallest at the tip.

4. Processing error feedback compensation

4.1 Experimental setup of error feedback compensation

In order to further reduce the machining error after cutting tool compensation, the error feedback compensation strategy is selected as shown in **Figure 15**. Two accelerometers are attached to the side of the stator of the main spindle and the side of the workpiece to measure their vibration signals respectively. The vibration of the accelerator attached to the main spindle in idle and working conditions is monitored and feedback to CNC, then, the CNC control the main spindle rotation speed to obtain minimum vibration signal. The vibration sensor attached to the workpiece monitored the dynamical performance of the workpiece and the signal is sent back to the control unit for processing. A servo actuator is attached to the bottom surface of the workpiece to compensate for the machining error, which is based on control signal received from control unit. An acoustic emission sensor is attached near the workpiece to monitor the acoustic noise and the fault processing condition. The original signal is sent to control main server for processing and pattern and status recognition. Lastly, the control command is sent from the main server to CNC machine to minimize the machine error.

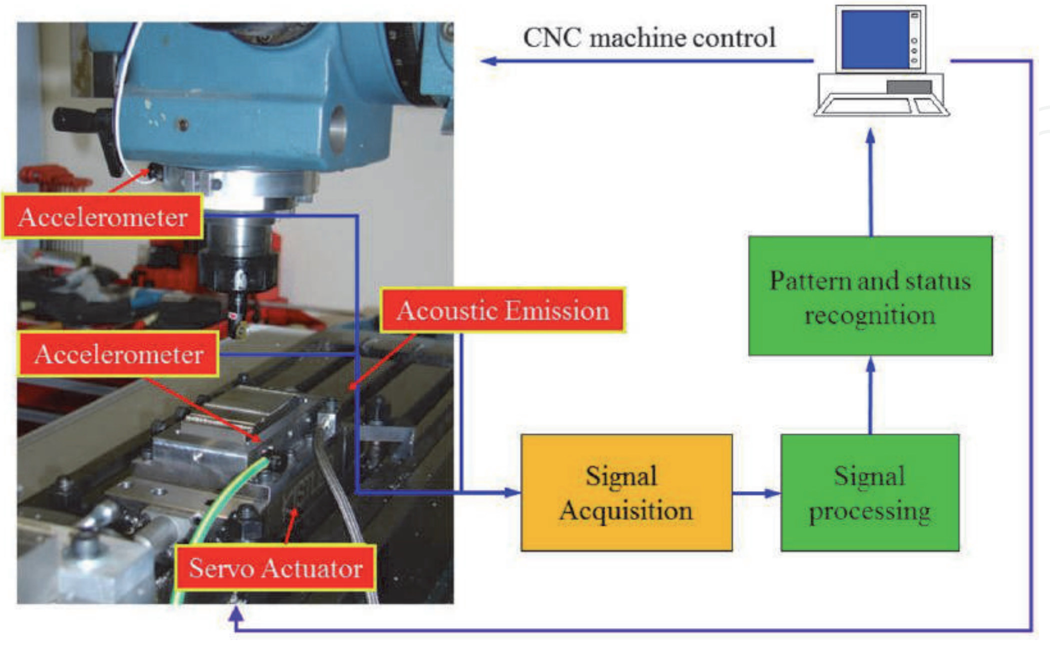

Figure 15.
Schematic of error feedback compensation.

4.2 Signal processing in error feedback compensation

Figure 16 shows error feedback compensation signal noise filter and reconstruction processing. The original time domain signal is obtained from the vibration sensor and converted into frequency domain through fast Fourier transform (FFT) algorithm. The bandpass filter is applied to filter out high frequencies and low-frequency and DC component. Interesting frequencies that include useful information are obtained after applying a signal technology to find peaks of the FFT in the range. The final step is to reconstruct the signal to control the actuator in order to compensate for machining error.

4.3 Experimental results of error feedback compensation

Figure 17 shows the cutting surface error without tool deflection compensation, with tool deflection compensation, and with error feedback compensation. It can be seen that the maximum machining error is reduced by 35% from 0.032 to 0.021 mm when the error feedback compensation is applied. Therefore, the total machining error is reduced by 60% from 0.53 to 0.021 mm. However, the error feedback strategy does not work at measurement point 40. Moreover, in two ranges (point 20–28, point 45–55), machining error is larger than that with tool deflection compensation strategy only.

The deviation distribution of machining without compensation, with tool deflection compensation, with error feedback compensation is shown in **Figure 18**. It can be seen that the deviation distribution of the machine curved surface with feedback compensation is minimal. On the other hand, the deviation distribution of the machine curved surface without tool deflection and error feedback compensation is largest. In other words, in order to achieve good machining quality product, the tool deflection compensation and error feedback compensation strategy should be adopted.

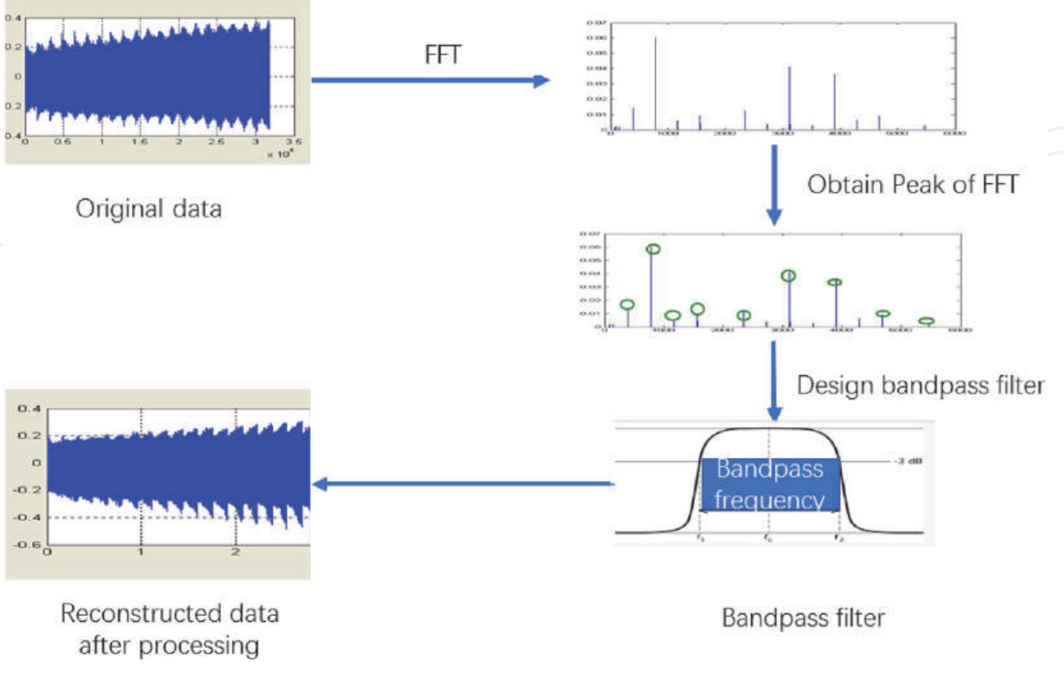

Figure 16.
Error feedback compensation signal noise filter and reconstruction processing.

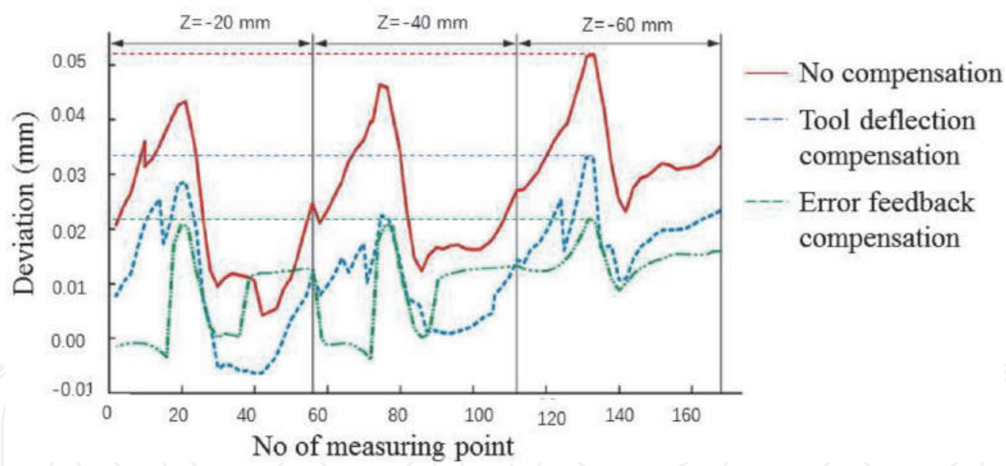

Figure 17.
The machining surface error without tool deflection compensation, tool deflection compensation, error feedback compensation.

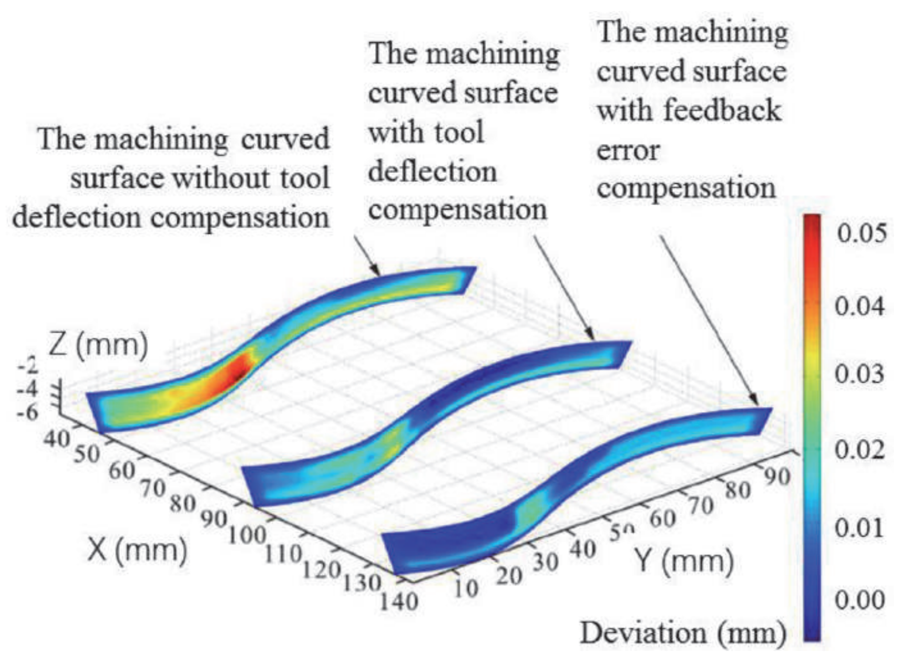

Figure 18.
The deviation distribution of the machining without compensation, with tool deflection compensation, with feedback error compensation.

5. Processing parameter optimization compensation

An experienced operator can significantly reduce machining error by applying cutting tool deflection and error feedback compensation when the optimized operation parameter is known. However, the process obtaining optimized operation parameter by try and error is time-consuming for new operator. Therefore, this section will introduce the parameter base optimization operation strategy. 5G AI edge computing and cloud computing strategy will be applied to obtain optimized operation parameter automatically.

5.1 Network configuration for processing parameter optimization

Figure 19 shows the cloud-based intelligent manufacturing configuration with 5G AI edge computing, which is also known as smart manufacturing configuration. The company data center managed by the IT department acts as a data transfer

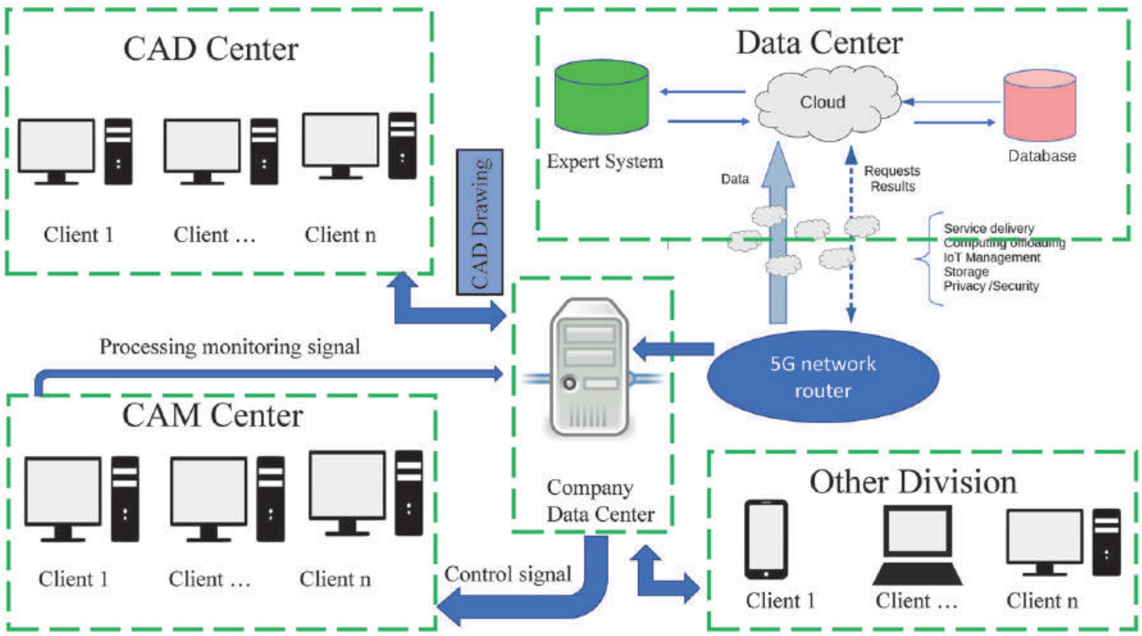

Figure 19.
The cloud-based intelligent manufacturing configuration.

bridge connecting each department of the company such as CAD center, CAM center, sales department, supply department, warehouse, maintenance department etc. It also acts as a data communication buffer linked to cloud computing centering out of the company. The designer can access the local data center to download the CAD drawing in order to modify the existing drawing, save the new CAD drawing, or update drawing to local data center. In the CAM center, every client computer is connected to a CNC machine. The CNC machine processing monitoring signal and the corresponding machine number information are sent to the company data center and to the cloud computing data center if necessary. All information needed for CAM center to produce the machining parts is sent through company data center as well. For instance, the production manager can download the CAD drawing from company data center and convert it to CAM file format. The technical person from the company then sends a file with control command or a file with the new compensation algorithm trained by cloud computing to the client PC in the CAM center. Cloud computing center receives request and the training data set from the company and sends back the proposed processing optimized parameters or processing control algorithm. In the cloud data center, the data received from the company will be stored in a database. It utilizes GP, MNNR, or other deep learning algorithm to obtain the optimized parameters through the expert system.

Figure 20 shows the cloud-based intelligent manufacturing configuration in the CAM center. The whole system configuration includes CNC real-time machining status monitoring, real-time environmental monitoring, CNC cutting tool deflection compensation, error feedback compensation as well as CNC machining operation process optimization through a combination of cloud computing and 5G AI edge computing. Unlike traditional standalone CNC machining, all CNC machines (refer to **Figure 21**) are connected through a local network client PC with cable or wireless in intelligent manufacturing environment. CAD drawing is sent to a local client instead of programming. The signals from sensors monitoring the CNC machining status are sent to 5G AI edge computing devices to pre-process. Processed data and corresponding machine no. are sent to the company data center through the client PC.

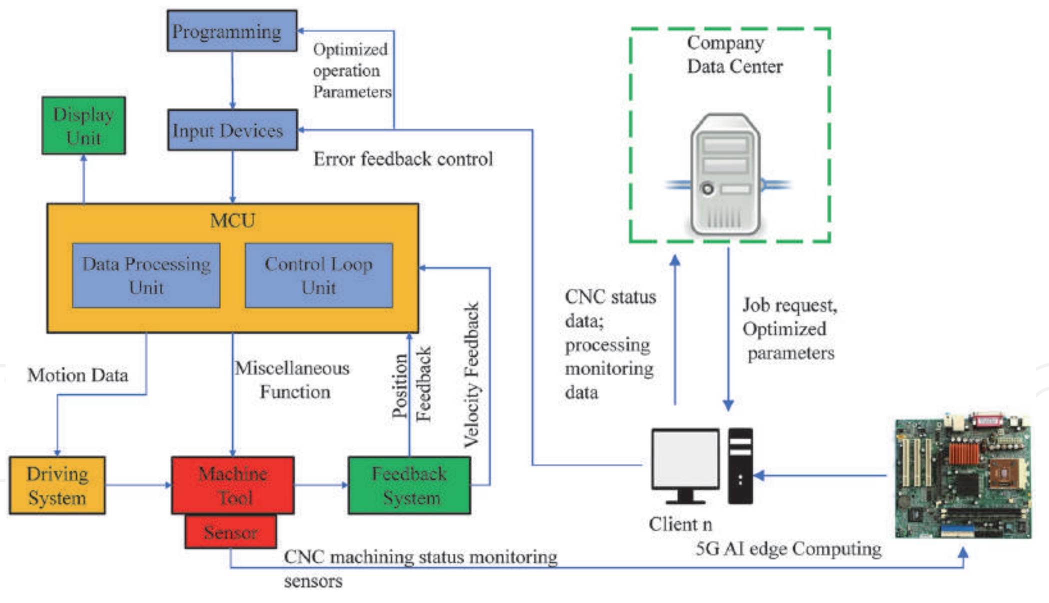

Figure 20.
The cloud-based intelligent manufacturing configuration in CAM center.

Figure 21.
A group of CNC machines connected through local networks.

5.2 Data collection for processing parameter optimization

Figure 22 shows a CNC machine connected to the local network. In order to obtain vibration signal to train the GP, Neural Networks (NNR), and Support Vector Machine (SVM) algorithm, two wireless accelerometers, Sensor 1 and Sensor 2, are attached to the cutting tool. Their signals will be sent to the cloud for GP, NNR, and SVM base computing. Specimen (Nylon) is clamped into three-jaw chuck. Vibration signal is sent to cloud server through 5G AI Edge computing device and 5G router. In order to find optimized operational rotational speed of main spindle, three groups of specimens (30 pcs) are machined with varied rotational speed as shown in **Tables 1–3**.

In order to get reliable data, the three groups of specimens must have the same experimental condition; the diameter and length of all experimental specimens are 25 and 30 mm respectively.

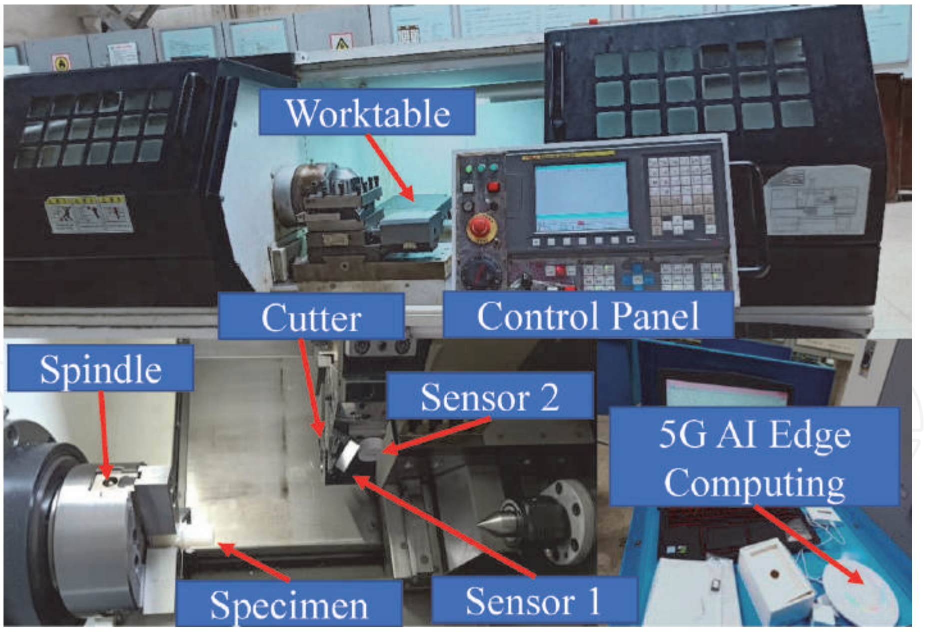

Figure 22.
Real-time monitoring of the CNC process in a production environment.

S/N	Diameter(mm)	Rotating speed (RPM)	Feed rate (r/min)	Length(mm)
A1	25	100	0.30	30
A2	25	300	0.20	30
A3	25	500	0.10	30
A4	25	700	0.08	30
A5	25	900	0.06	30
A6	25	1100	0.05	30
A7	25	1300	0.05	30
A8	25	1500	0.03	30
A9	25	1700	0.02	30
A10	25	1900	0.01	30

Table 1.
Group A specimens with varied machining parameters.

When the rotating speed of the main spindle of CNC machine is the same, the same feed rate is selected as well. The feed rate is increased with increasing rotating speed.

Figure 23 shows three groups of specimens labeled as A1–A10, B1–B10, and C1–C10 respectively. Group A specimens are used as training data set while group B and C specimens are used as testing data set.

5.3 Signal processing technologies for processing parameter optimization

There are various signal processing technologies for analyzing the monitoring machine working condition and product processing. The commonly used technologies are: time domain signal processing; FFT; wavelet technology; and short-time Fourier transform (STFT). Normally, time domain data are the original data recorded by the sensor, FFT is the technology developed to convert time domain

S/N	Diameter(mm)	Rotating speed (RPM)	Feed rate (r/min)	Length(mm)
B1	25	100	0.30	30
B2	25	300	0.20	30
B3	25	500	0.10	30
B4	25	700	0.08	30
B5	25	900	0.06	30
B6	25	1100	0.05	30
B7	25	1300	0.05	30
B8	25	1500	0.03	30
B9	25	1700	0.02	30
B10	25	1900	0.01	30

Table 2.
Group B specimens with varied machining parameters.

S/N	Diameter(mm)	Rotating speed (RPM)	Feed rate (r/min)	Length(mm)
C1	25	100	0.30	30
C2	25	300	0.20	30
C3	25	500	0.10	30
C4	25	700	0.08	30
C5	25	900	0.06	30
C6	25	1100	0.05	30
C7	25	1300	0.05	30
C8	25	1500	0.03	30
C9	25	1700	0.02	30
C10	25	1900	0.01	30

Table 3.
Experimental specimen group C with varied machining parameters.

data to frequency domain data. The wavelet technology is commonly used to decompose a complex signal to sleeve sub-level simple signals. STFT is the signal processing technology developed to overcome the drawbacks of FFT. In most cases, it is used to monitor the transition signal. In this section, each signal technology will be discussed based on experimental data. The purpose is to find out the most suitable signal processing technology to develop process parameter optimization.

Sensor 1 is attached to the tip of the cutter to monitor the cutting dynamic force-induced vibration. The sensor is a wireless accelerometer and powered by a built-in battery. As shown in **Figures 24** and **25**, time domain signal is repeatable with signal noise. However, we cannot trace enough useful information from the signal in time domain.

Due to lack of useful information from time domain data, frequency domain data are converted from time domain data by employing FFT technology. In machine fault diagnosis application, the fault frequencies can be found when the machine is under faulty working condition such as bearing wear and tear.

Figures 26 and **27** show the frequency domain data of Sensor 1 in X and Y directions, respectively. The domain frequency is the 1x order signal frequency, which is around 31.67 Hz. The second contribution signal is around 263 Hz. The third and fourth ones are that of 2x order and 3x order signal respectively.

Figure 23.
Experimental specimen groups with varied machining parameters.

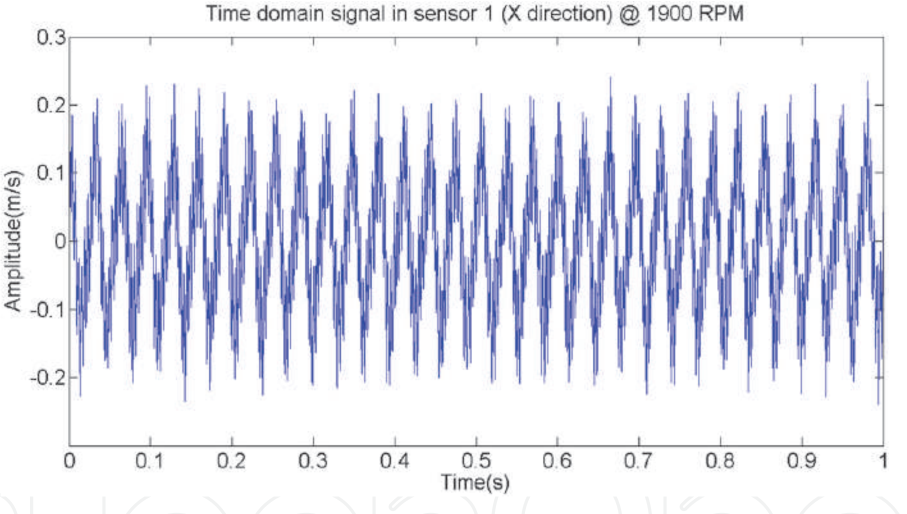

Figure 24.
Time domain signal in Sensor 1 in X direction.

Wavelet technology is originally developed to decompose complex signal. It may be used in the processing application to trace useful information. **Figure 28** shows wavelet spectrum in sensor 1 in X and Y directions; it can be seen that the signal is decomposed. However, only first two domain signals can be displayed. Moreover, the frequency of each signal cannot be recognized, which means this signal technology may be not suitable for processing optimization application. Other signal technologies should be further studied to be applied in this application field.

Figure 29 shows short-time Fourier transform spectrum in sensor 1 in X and Y directions. It can be seen that the dominant signal is the low-frequency component. However, it cannot provide any useful information for optimizing processing parameters. In **Figures 26** and **27**, we know that the dominant frequency is the 1x order of main spindle rotating frequency. Waterfall technology is used to apply FFT in several steps of the main spindle's rotational speed in order to trace any changes due to change in rotating frequency.

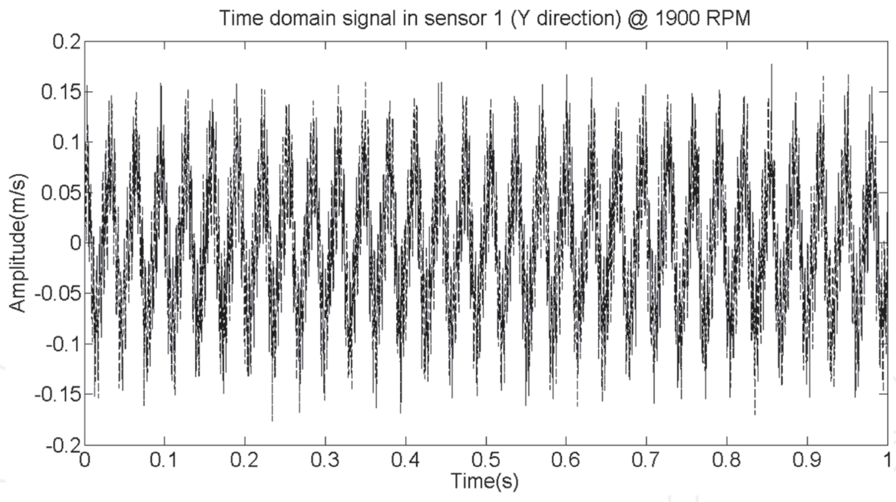

Figure 25.
Time domain signal in Sensor 1 in Y direction.

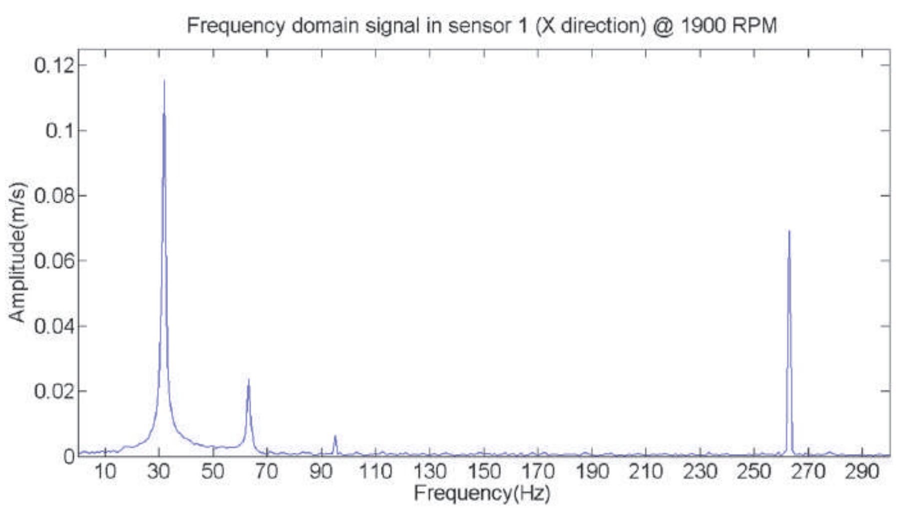

Figure 26.
Frequency domain signal in Sensor 1 in X direction.

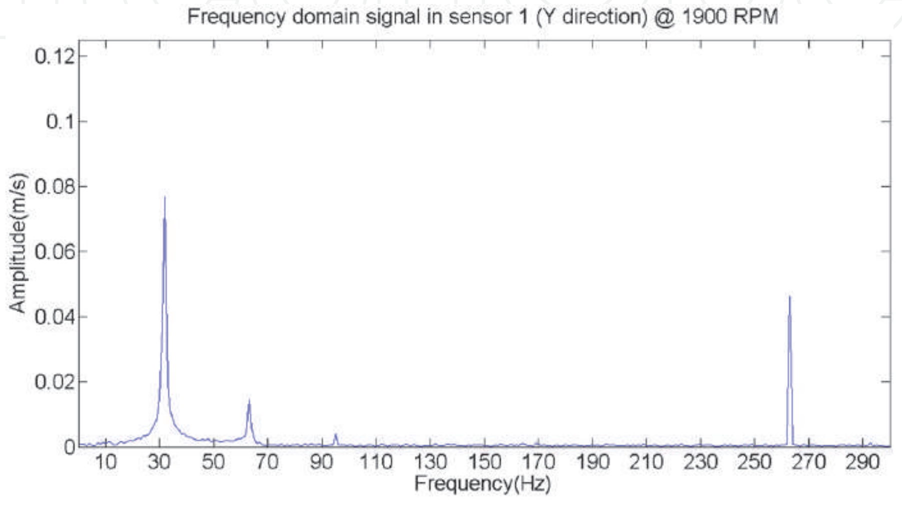

Figure 27.
Frequency domain signal in Sensor 1 in Y direction.

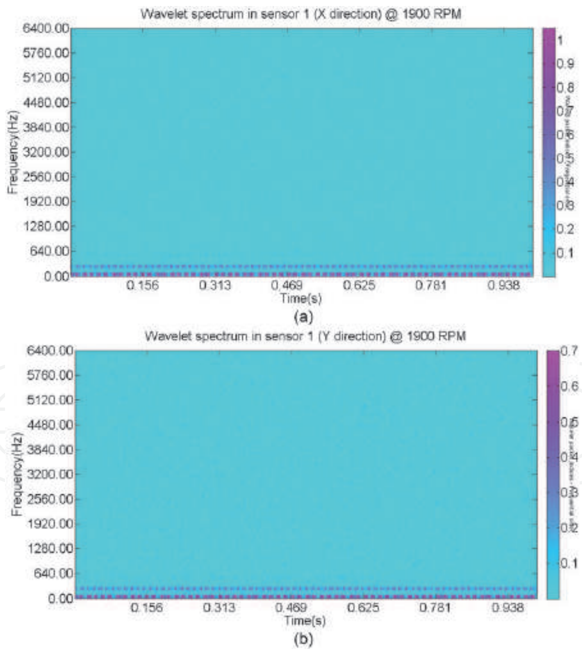

Figure 28.
Wavelet spectrum in Sensor 1 in X and Y directions.

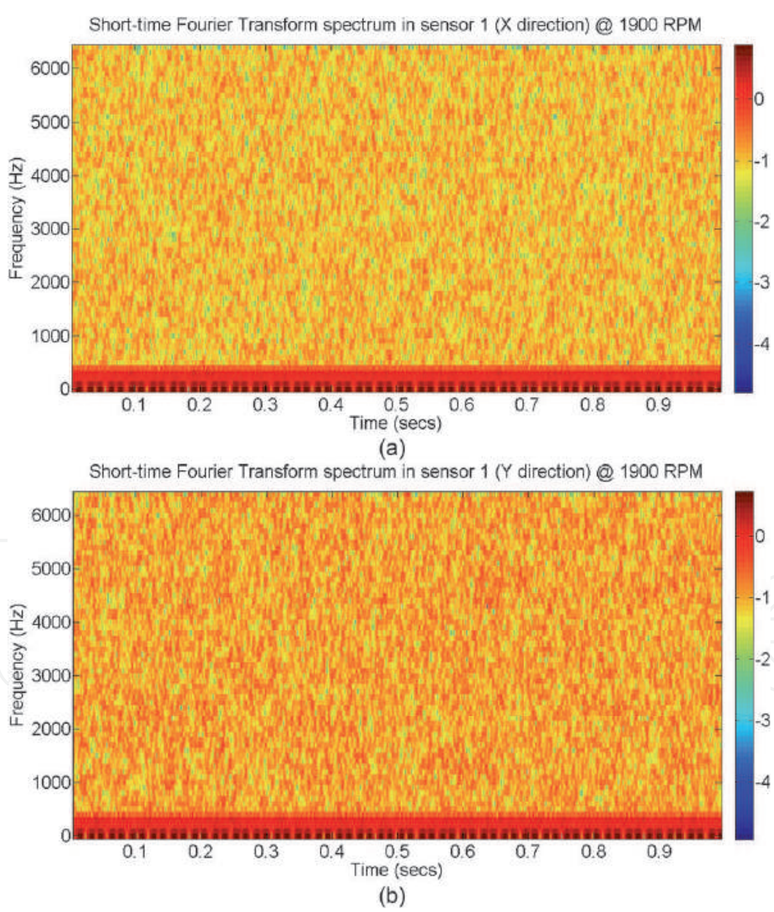

Figure 29.
Short-time Fourier transform spectrum in Sensor 1 in X and Y directions.

5.4 Experimental results of processing parameter optimization

The useful information is traced when the waterfall of speed spectrum is developed.
Sensor 1 is attached to the tip of the cutting tool to monitor the cutting dynamic force-induced vibration. **Figures 30** and **31** show the vibration in X and Y directions

respectively. In **Figure 30**, it can be seen that the dominant frequency components are 1x, 2x, and 3x. Moreover, the maximum value is 0.12 mm/s at 31.6 Hz and the vibration spectrum is increased with increasing rotating speed. The lowest resonance frequency of the CNC machine is 263 Hz. Therefore, the machine rotating speed has to deviate far away from 15,780 rpm.

In **Figure 31**, the maximum value is 0.08 mm/s at 31.6 Hz. Under 1900 rpm, the maximum value is smaller at 31.6 Hz, as the cutter bears bigger cutting force due to removal of material by cutter in X direction.

Sensor 2 is attached to the base of the cutting tool to monitor the cutting dynamic force-induced vibration. **Figures 32** and **33** show the vibration in x and y direction respectively. It can be seen that the maximum vibration of Sensor 2 is 0.025 and 0.16 mm/s in x and y direction respectively, both smaller than that of Sensor 1. Therefore, the vibration signal of Sensor 1 is more sensitive and is a better candidate than Sensor 2 for monitoring the CNC machine working status. Furthermore, only the frequency domain dominates frequencies and their amplitudes are selected to be sent to the cloud in order to reduce data size and increase data transmission rate.

After the speed spectrum is obtained, the frequencies and their peak value can be obtained by applying data mining methodology. **Figure 34** shows the tracing peak

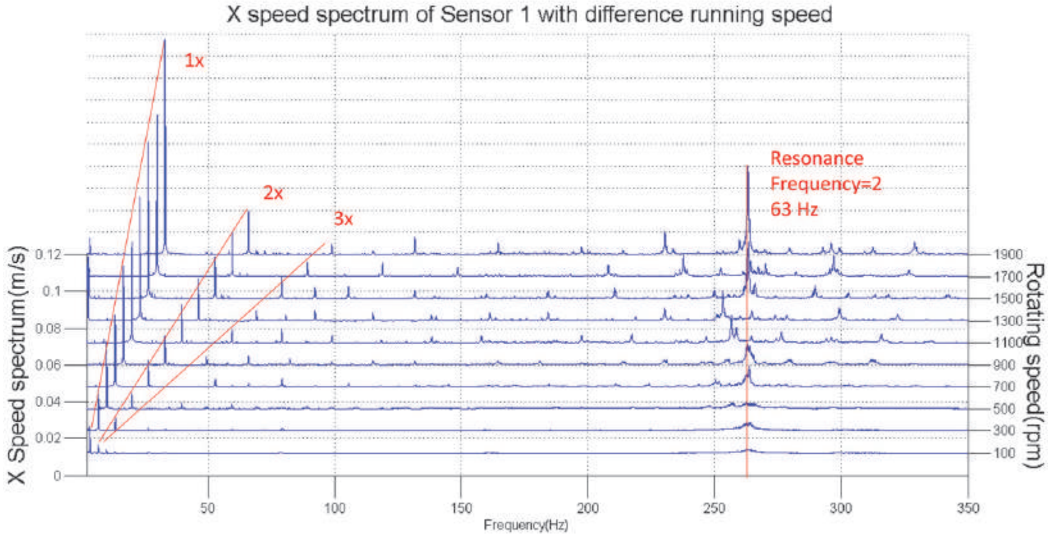

Figure 30.
Vibration signal in X direction of Sensor 1.

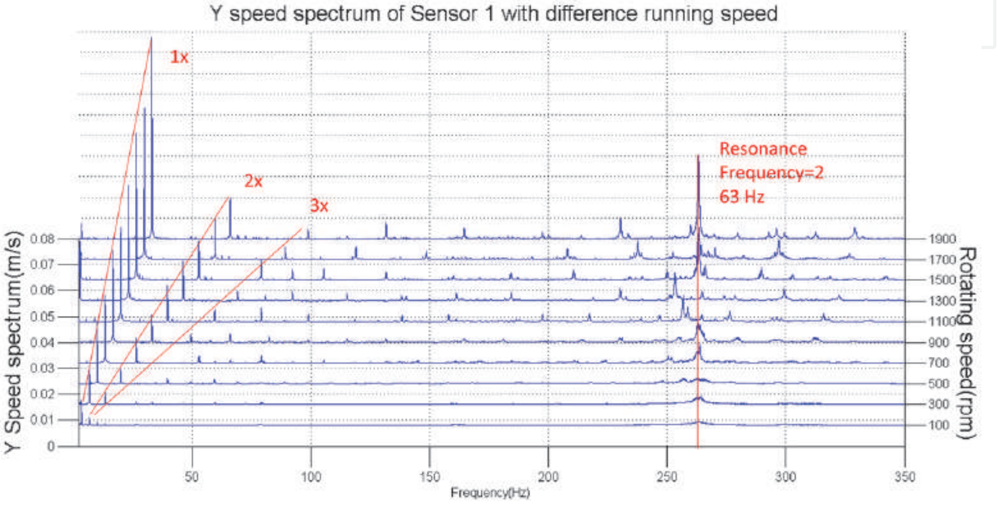

Figure 31.
Vibration signal in Y direction of Sensor 1.

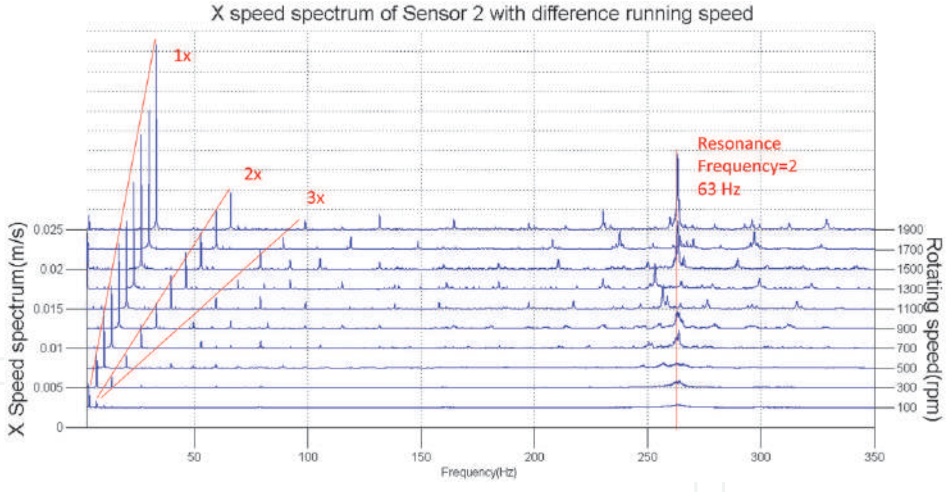

Figure 32.
Vibration signal in X direction of Sensor 2.

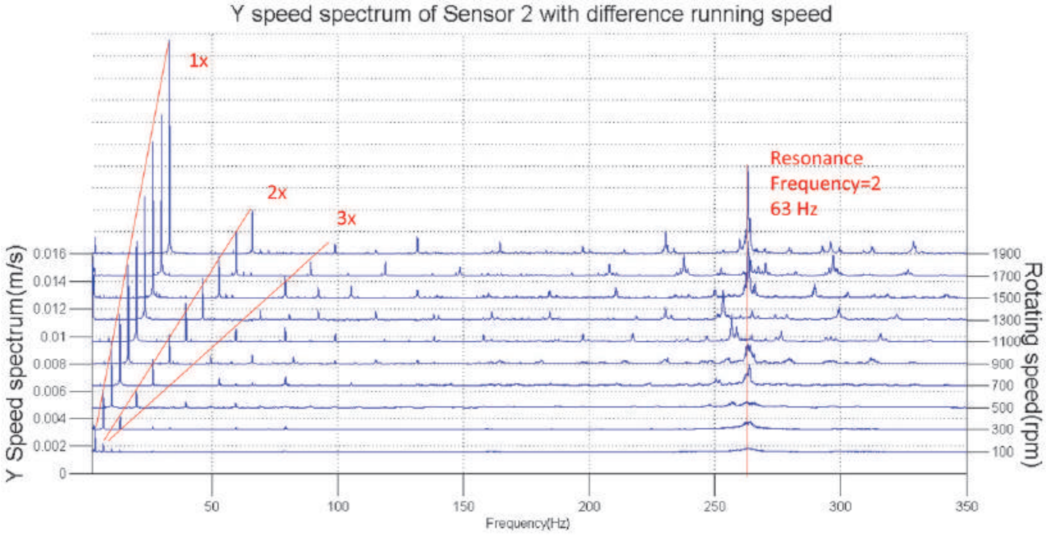

Figure 33.
Vibration signal in Y direction of Sensor 2.

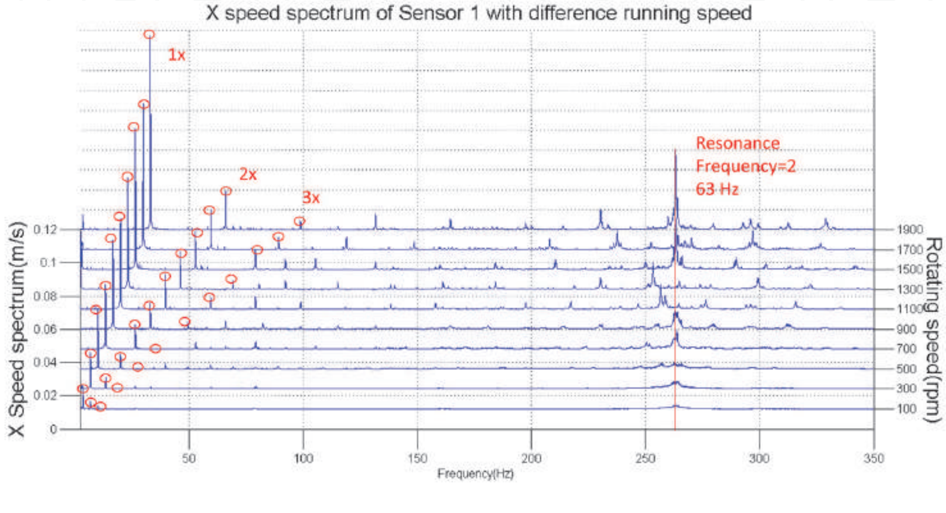

Figure 34.
Tracing peak values of group a specimens in frequency domain.

values of group A specimen in frequency domain with interesting 1x, 2x, and 3x data. The peak values of specimen A, B, and C are shown in **Tables 4–6** respectively.

The experimental parameters such as material, dimensions, temperature, reaction forces, vibration data, and machining quality such as tolerances will be sent to the Multilayer Artificial Neural Network (MANN) to train the optimized operation parameters. The MANN is shown in **Figure 35**.

Figure 36 shows results of MANN training based on training data, the training correction is about 99%. If more training data are adopted, the trained MANN should be more accurate.

Figure 37 shows general data classification results based on deep learning; there are four types of results: (a) The machining result is linearly classified into two

S/N	Rotating speed (RPM)	1st vibration in X (mm/s)	2nd vibration in X (mm/s)	3rd vibration in X (mm/s)	1st vibration in Y (mm/s)	2nd vibration in Y (mm/s)	3rd vibration in Y (mm/s)
A1	100	0.01349	0.00433	0.001583	0.00899	0.00288	0.001055
A2	300	0.02196	0.00683	0.001353	0.01464	0.00455	0.000189
A3	500	0.03635	0.00834	0.003509	0.02424	0.00566	0.0001864
A4	700	0.03911	0.01471	0.00283	0.02608	0.00981	0.000159
A5	900	0.05354	0.01576	0.004258	0.03569	0.01051	0.002839
A6	1100	0.05495	0.02097	0.006776	0.03663	0.01398	0.004519
A7	1300	0.06709	0.02301	0.005445	0.04473	0.01534	0.003630
A8	1500	0.08472	0.02256	0.01205	0.05661	0.01504	0.008036
A9	1700	0.08787	0.02442	0.007477	0.05858	0.01628	0.003930
A10	1900	0.11650	0.02332	0.005225	0.07771	0.01424	0.003484

Table 4.
Vibration speed spectrum of group A specimen.

S/N	Rotating speed (RPM)	1st vibration in X (mm/s)	2nd vibration in X (mm/s)	3rd vibration in X (mm/s)	1st vibration in Y (mm/s)	2nd vibration in Y (mm/s)	3rd vibration in Y (mm/s)
B1	100	0.01227	0.00393	0.001389	0.00856	0.00289	0.000955
B2	300	0.01996	0.00625	0.001356	0.01392	0.00457	0.000159
B3	500	0.03305	0.00768	0.003509	0.02375	0.00522	0.000176
B4	700	0.03556	0.01389	0.003871	0.02548	0.00919	0.000168
B5	900	0.04867	0.01435	0.006163	0.03446	0.00985	0.002762
B6	1100	0.04996	0.01906	0.004949	0.03438	0.01356	0.004327
B7	1300	0.06099	0.02091	0.005445	0.04293	0.01415	0.003403
B8	1500	0.07723	0.02051	0.005691	0.05308	0.01438	0.007534
B9	1700	0.07989	0.02221	0.005377	0.05492	0.01526	0.004673
B10	1900	0.10590	0.02128	0.004725	0.07284	0.01458	0.003266

Table 5.
Vibration speed spectrum of group B specimen.

S/N	Rotating speed (RPM)	1st vibration in X (mm/s)	2nd vibration in X (mm/s)	3rd vibration in X (mm/s)	1st vibration in Y (mm/s)	2nd vibration in Y (mm/s)	3rd vibration in Y (mm/s)
C1	100	0.013776	0.004561	0.001615	0.00969	0.00309	0.001135
C2	300	0.022455	0.008512	0.001489	0.01597	0.00483	0.000160
C3	500	0.037152	0.009501	0.003332	0.02594	0.00595	0.000166
C4	700	0.039975	0.016095	0.003891	0.02748	0.01059	0.000168
C5	900	0.054656	0.021396	0.005345	0.03825	0.01259	0.003065
C6	1100	0.056174	0.020348	0.006918	0.03945	0.01489	0.004847
C7	1300	0.068568	0.021915	0.005555	0.04795	0.01645	0.003989
C8	1500	0.086655	0.020513	0.007123	0.06069	0.01668	0.008615
C9	1700	0.089672	0.024926	0.007635	0.06278	0.01756	0.005341
C10	1900	0.118923	0.023856	0.005332	0.08325	0.01569	0.003732

Table 6.
Vibration speed spectrum of group C specimen.

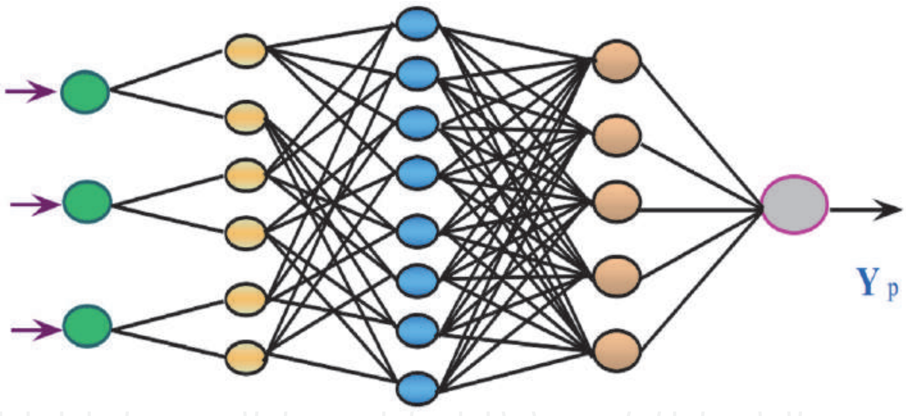

Figure 35.
Multilayer artificial neural network (MANN).

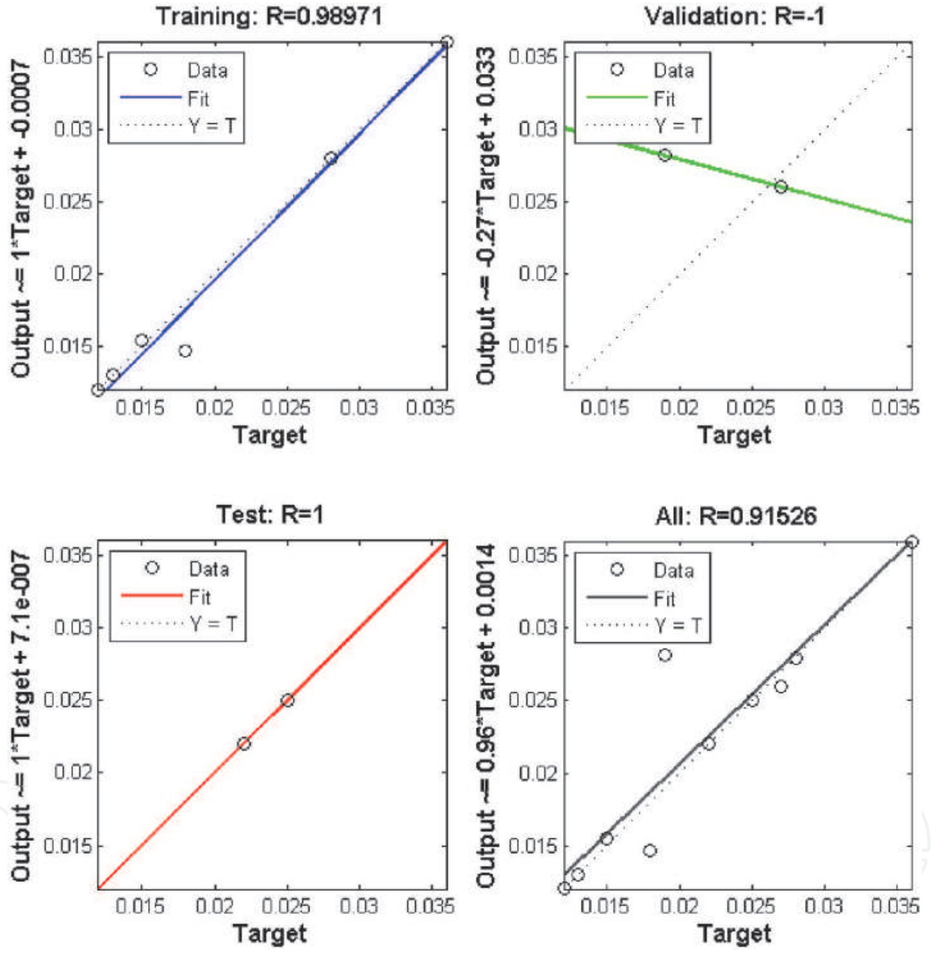

Figure 36.
Results of multilayer artificial neural network (MANN) training.

groups: one that met the quality requirements and one that failed to meet the quality requirements. (b) The result is linearly classified into three groups as low, medium, and high rotation speed range. In low and high rang, the machining quality cannot meet the quality requirement. Sometimes, the machining quality classification is not linear as shown in (c). The classification quality is not only based on deep learning technology but also depends on the quantity of parameters and the machining material. The matching quality can be further classified into grades of quality such as grade A, B, and C, as shown in **Figure 36**, based on machining tolerances.

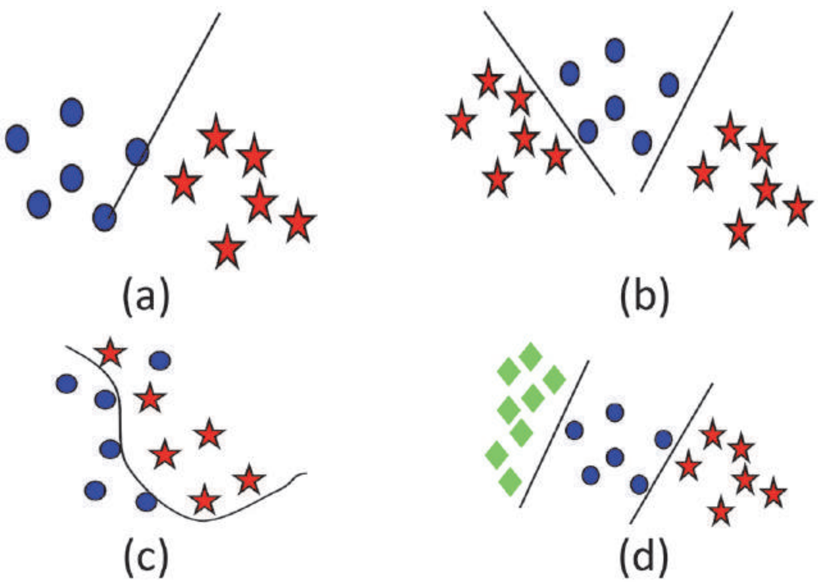

Figure 37.
Data classification results based on deep learning. (a) Two classes linear classification, (b) multi-classes classification, (c) two classes no-linear classification, and (d) multi-classes no-linear classification.

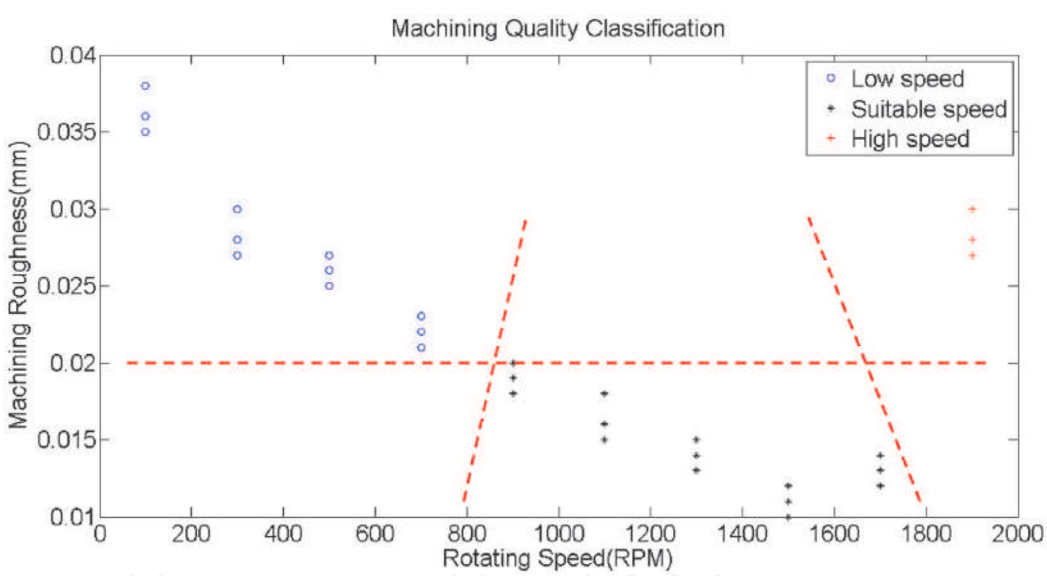

Figure 38.
Classification results of machining nylon with varied speed of CNC.

Figure 38 shows classification results of machining Nylon with variable speed of CNC based on deep learning. If the machining roughness threshold is set as 0.02 mm, the spindle speed of CNC should be more than 900 rpm and less than 1800 rpm.

6. Conclusions

This chapter presents our research studies on a parameter optimization method of product processing procedure for CNC machine tool with three common systematic errors compensation approaches.

In Section 1, we introduced mechanism optimization, energy consumption optimization, and processing optimization of a CNC machine tool. Mechanism optimization is mainly used to optimize the CNC machine tool to reduce machine systematic errors. On the other hand, due to huge electrical energy consumption of CNC machine tool under operational mode, energy consumption optimization should be considered. There are tremendous researches on the first two aspects but less on the last one. Therefore, in the next section, our studies focus on the processing optimization approach.

In Section 2, we briefly introduced the working principle of CNC machine tools. In order to reduce machining error, the cutting force has to be monitored constantly. The machining of the complex surface can be decoupled into simpler ones for path optimization in order to minimize speed fluctuation-induced machining error. For the same purpose, machining tool overcutting compensation and two major indicators S_t and S_q of the machining accuracy are introduced and an optimized profile is proposed.

In Section 3, we studied tool deflection issue during machining. The merits and drawback of two commonly used displacement sensors, capacitive probe and eddy current gap sensor, are compared and recommended for different scenarios. In this section, 5G AI edge computing technology for signal pre-processing and genetic programming for control algorithm parameters optimization are proposed. The experimental results with tool deflection compensation are reduced by 40%.

In Section 4, we studied error feedback compensation approach. The CNC and servo actuator are in the close loop for error feedback compensation. A bandpass filter is adopted to reduce the noise in order to reconstruct the control signal. The experimental result is reduced by 60%.

In Section 5, we studied processing parameter optimization. The cloud-based intelligent network configuration for processing parameter optimization is proposed. In this section, the method is mainly based on deep learning approach such as GP, MANN, and SVM to identify the product processing optimized parameters. Before deep learning approach is employed in cloud computing with expert system and database, all the information in the train data instance such as raw material type and dimensions, CNC machine tool systematic parameters, and machining operational conditions and vibration outputs of the CNC machine tool must be sent to a cloud-based computing center. The amplitudes and frequencies of the CNC machine tool outputs are determined by the waterfall of FFT after the signal is preprocessed through 5G AI edge computation. The functionality and performance of the proposed technique are verified with simulations as well as with the experimental data and results, which proves the effectiveness of the proposed scheme.

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Chapter

Interlinking Industry 4.0 and Academia through Robotics and Automation: An Indian Perspective

Prajwal Prabhu, Subin Raj and Abhra Roy Chowdhury

Abstract

Robots and automation systems are growing rapidly in the society globally with an annual global sales value of 16.5 billion USD in 2018 according to the International Federation of Robotics (IFR). They have found a commonplace not only in industries and service sector but also in households. This has attracted heavy investment by industries globally in the research and development of robotics and its applications. Understanding this rising trend in the industry and society, there is an obvious need for expertise and future workforce in robotics. According to the IFR report, India has recorded a growth of 39% in 2018 compared to the previous year in terms of annual robot installations. The annual report of the Confederation of Indian Industry (CII) in 2019 recommends robotics and automation as one of the prime areas of focus toward the development of national policies on Industry 4.0. One such interlinking initiative in robotics research and innovation has started at the Centre for Product Design and Manufacturing (CPDM) in the Indian Institute of Science (IISc). The project is designated under India's first Industry 4.0-compliant Smart Factory R&D platform in a unique academic set-up. It aligns with the policies of Govt. of India to boost vision Industry 4.0 for India's technological and economic transformation.

Keywords: Industry 4.0, robotics, automation, autonomous systems

1. Introduction

With the advent of industrial development, humans have witnessed its four phases starting from mechanized processes, mass production using electricity, assembly lines and now finally culminating to Industry 4.0. It is also commonly referred as Smart factory where the physical processes of factory are monitored by decentralized cyber-physical systems to take autonomous and individual decisions. The physical systems i.e. machines are configured with the Internet of Things (IoT), communicating in real time to each other and with human operators over the web representing another vital component called interoperability. Indian Institute of Science (IISc) has been developing a "Smart Factory called I4.0India@IISc" that will act as a Common Engineering Facility Centre (CEFC) at the Centre for Product Design and Manufacturing (CPDM), under the SAMARTH Udyog Bharat 4.0 program of the Department of Heavy Industries (DHI), GoI in [1].

The CEFC builds on the earlier work at IISc that initiated India's first smart factory R&D platform with seed collaboration fund from the various multinational and national companies worldwide. The CEFC intends to develop two contrasting factory platforms. One is highly automated, with data-intensive processing machines such as 5-axis CNC, metal additive manufacturing, metal laser routers etc. that are handled by Industrial robots, collaborative robots, automated guided vehicles, etc. The other platform is highly manual, with legacy machines with data layer, where handling is also carried out manually. The distinction is that all elements in both the Platforms (people, process, parts, tools and environment) are to be connected via IoT-based communication networks and data are stored and analytics carried out using cloud computing. The intent is to use the platforms as demonstration centers in which factories of the future will be explored to see their potential and challenges, and use the platforms for advancing research, innovation, training and support for practice. A major aim of this CEFC is to support Industry 4.0 in MSMEs of India by developing "advanced yet affordable" technologies and solutions for their use. The CEFC is supported by Tata Consultancy Services (TCS), Yaskawa, Faurecia, Toyota Kirloskar Motors (TKM) and Ashok Leyland as industrial partners who contribute with fully funded research projects. The CEFC is also supported by faculty members drawn from 12 departments of IISc as collaborators. A variety of research-intensive technologies are being developed at the CEFC for the benefit of industry. The technologies under development include smart resource bins for waste tracking, smart inspection systems, AR/VR-based digital twins and digital walkthrough systems, 3D printing systems for printing devices with embedded electronics, PCB assembly support systems, multi-modal robots, affordable door localization systems, etc. The CEFC is meant to serve the following purposes:

- Use of the factory with its two platforms as demonstrators for Industry 4.0 (development of platform should be completed in next 6 months)

- Utilization of the platforms for trying out new building blocks, technologies and solutions for their potential effects on KPI before committing investment on these.

- Playing with various combinations of the two platforms for creating different variants of factories of the future and seeing their impact on KPIs.

- Using the factory as a springboard for supporting development of new innovations and start-ups for Industry 4.0 (1 start-up initiated, 10 existing start-ups already supported as planned)

- Creating Indigenous R&D capabilities in the area for India's Industry 4.0 by training researchers and developing deep tech knowledge. (11 PhD students and 20 researchers are being trained, over 20 technologies, tools and solutions are being developed with industrial significance)

- Providing awareness, training and education, especially high-end training to develop future leaders in manufacturing (over 500 people already trained, which is 2.5 times more than originally planned; a new MTech and PhD program in manufacturing initiated at IISc, an international conference on Industry 4.0 and Advanced Manufacturing I-4AM'19 initiated)

In continuation to this we have identified the opportunities and challenges for human robot collaboration in Industry 4.0 set-up. This is mentioned in subsequent sections.

2. Human factors in logistics and warehouse industry

A supply chain in a manufacturing environment involves manufacturers, suppliers, and other logistical entities that would entail dealing with the customers' requests. Modern management practices are designed to reduce the inventories; thus, warehouses play a crucial role in customer services and product availability. Logistical support provided to improve the warehouse order picking scenario would entail reduction of time in retrieving of the object and its successful shipment for delivery. Customer satisfaction in such a scenario would require for an efficient and flexible warehouse order handling processes. However, any small changes in the customer end of the supply chain would create a large ripple in the stock levels and orders along the supply chain also called as a "Bullwhip Effect." Increasing demand at the nth tier in a supply chain will be over-compensated by an even greater increase of the demand at the n+1th tier of the chain in [2]. As a result, the curve mapping the stock levels along the time looks similar to a whiplash, hence the name "Bullwhip Effect." Some of the key aspects of the human factors in the logistics industry are quantified as Perceptual Factor, Mental Factor, Physical Factor, Psychological Factor in [3]:

1. Perceptual Factor: Perception to new things will play a role to changing needs of warehousing environment. This will play a very important factor in determining the overall productivity of the warehouse. This factor will amount to 24.4% in the order picking process. Some of the key things that will affect in this factor would include information technology, ability to read, confusion created due to negligence and ability to accept new technology. It is of the utmost importance that the laborers are skilled to understand the upcoming technology that will reduce the overall burden of their work.

2. Mental factor: The mental factor in any order picking process will be of maximum importance and will amount to 45.2% in the order picking process. Some of the key aspects in this factor would be as follows: cognitive ability, ability to learn new technology will be a very important factor to ensure that the order picking process can be done in a very efficient way and will amount to 37.3%. Some of the other factors include behavior, training. To ensure the productivity of the warehouse, the laborers should have decent working environment where they are more receptive and learn modern technologies and new ideas that will improve the efficiency of the system.

3. Physical Factor: The physical factor in order picking process will amount to 16.3%. Some of the key aspects that will affect the order picking process are: Having an improper workload will lead to musculoskeletal diseases in the human beings causing back pain and fatigue. Further improper material handling may lead to material damages that will increase the overall cost in the production. It is of utmost importance that the workload of all laborers should be uniformly distributed, to avoid the breakdown of the warehouse machinery.

4. Psychological Factor: Factors like work environment, stress, monetary incentives also play a very important role in ensuring that human beings are motivated to do quality work and ensure that the order handling process runs in a very smooth and efficient way. Laborers should have proper incentives and can be in the form of monetary or otherwise, to ensure that they are motivated throughout to ensure that the productivity of the warehouse is not dropped.

3. Indian scenario for the human factors in logistical/warehousing industries

Logistical cost in Indian scenario accounts to 13–17% of the overall GDP, which is nearly double the GDP of the developed countries like US, France, UK, etc. in [4]. Main reasons for such high costs are due to lack of efficient transport systems. Further it is seen that there is a limited focus on robotics and automation which would reduce the majority of the human works. The main percentage of the logistical cost in India is borne by the end users. The future trends in warehousing industry would involve companies consolidating large warehouse spaces and developing futuristic technologies that would improve the warehousing operations leading to better and efficient productivity. A huge amount of flexibility can be incorporated by including human operators in the warehousing industry. Human being can react quickly to any operational changes or urgent requirements of the orders and maneuver in tight spaces that lead to efficiency in the order picking systems. Some of the key measures taken by the Indian government to improve the logistical scenario in India include the Creation of exclusive Warehousing Promotion Zones. Create logistics and warehousing policies separate from industrial promotion policies, Allocation of areas exclusively for warehousing within Industrial Parks, Setting up of Skill Augmentation Centers in [4]:

1. Creation of exclusive Warehousing Promotion Zones: To create modern warehouses and facilitate modern warehousing, need to create exclusive warehousing zones is stressed to develop modern warehousing infrastructures.

2. Create logistics and warehousing policies separate from industrial promotion policies: State governments are mandated to form separate policies for development of the logistics and warehousing industry so that the industries can grow to its full potential.

3. Allocation of areas exclusively for warehousing within Industrial Parks: Adequate storage facilities for raw materials and finished goods need to be provided in the industrial parks where the manufacturing facilities are provided.

4. Setting up of Skill Augmentation Centers: It is of the utmost importance to set up a skill augmentation center so that warehouses can be modernized to improve productivity and efficiency. Some of the modern technologies that can be included in the warehousing include using of cloud to access the warehouse inventories, deployment of drones in the warehousing industry. Using of IoT and automation can improve the overall performance of the system.

4. Need for autonomous mobile robot in manufacturing industries

Automation in the manufacturing industry will ensure that the end result will be achieved in a more effective way thereby reducing the human effort. Automated guided vehicles are the most extensively used robots in the industry; however, these lack the self-regulating mobility and need navigation lines along the shop floor. Further material handling while using the AGV will require human effort which in some cases will reduce the productivity. The need for human operators to undertake planning activities and the lack of real time feedback of the shop floor's inventory level will make the efficient flow of materials tough.

Autonomous mobile robots are machines designed to maneuver itself in an obstacle filled environment through the use of sensors and feedback. Due to its design it can be used in manufacturing industry thereby reducing wear and tear in different industrial components and improve the productivity. AMR's provide a wide range of advantages such as: reduced floor traffic, flexibility, reliability, self-regulating mobility etc. in [5].

The need for using the autonomous mobile robots in manufacturing environment is as follows:

1. To increase productivity and efficiency
2. To improve material handling
3. To improve the safety of human operators in high risk, stress environments
4. To perform repetitive tasks so that the human beings can concentrate on cognitive and creative tasks.
5. To enhance overall revenue by delivering order in perfect fulfillment rates and better customer satisfaction.
6. To reduce the factory traffic by navigating in tight and complex environments.

5. Human robot interactions in logistics/warehousing industry

Human machine interaction is one of the most crucial aspects of the warehousing industry. Since there is a collaboration between human and machine in the warehousing industry, efficient interaction between the two systems would ensure that the process runs in a smooth way in [6]. In an HMI system, machines relieve human from performing repetitive tasks, and human can focus on working in creative and cognitive tasks. Thereby such collaborations would improve the efficiency and reliability of the overall system. Human beings will not be able handle heavy objects in the warehousing industry. Such things will lead to the musculoskeletal damage in human beings and factor into improper material handling. The advent automation has reduced the burden on the human in the warehousing industries. However, there is a reduction of skill in the warehouse workers due to the increased workload on the human beings in [6]. Thereby creating a concept of adaptive automation where there is a continuous interaction between the human and machine considering the ever-changing needs of a logistics/warehousing setup.

Figure 1 shows the possible types of interaction in human machine system, which is adapted from "Formalizing Human–Machine Interactions for Adaptive Automation in Smart Manufacturing" [6].

In general, the possible human interactions that are seen in a warehousing environment can be classified as Human machine interaction, Human task interaction, Supervisor system interaction in [6].

Typical human machine interaction system would consist of human supervisor, several manufacturing cells that and each cell consists of human operator, machine and a human machine interface. The whole system can be viewed as a cell layer and supervisor layer. The interfaces at the cell layer are associated with the UIs for human operators who manipulate the machines to achieve the logistical goals and respond to unexpected situations either by reporting unanticipated events to the supervisor or performing the exception handling tasks issued by the supervisor.

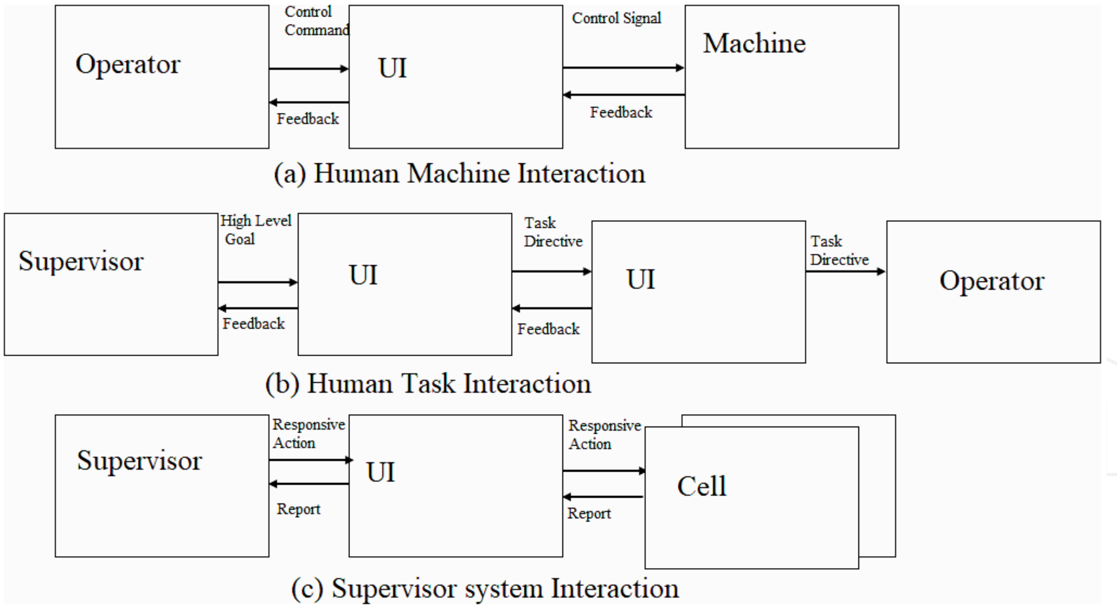

Figure 1.
Description for a human-machine system based on the type of interaction.

Information about machine state is delivered to the human operator through the interface and the operator controls the machine directly through his commands and suitably maneuvers the machine. The operator will notify the supervisor about any interrupts that may affect the overall performance of the system thereby allowing the supervisor to perform exception handling tasks. The interfaces at the supervisor layer are for a human supervisor in the human machine system. In normal scenarios the supervisor will monitor the key monitoring indices for logistical warehouses and maintain the task progress. In cases of exceptions the supervisor has to advice the operator to take the corrective actions. Exception handling task supportability is associated with responsive management concerning the uncertainty inherent in almost every logistical system. Designing of Human machine systems should take into account that human machine system has to assist humans or supervisor in coping with an unforeseen scenario. Due to a high degree of complexity, the problems of exceptions only by the means of autonomous robots will be a challenge, thereby creating the need for human involvement.

6. Present problems in autonomous navigation in factory set-up

Due to the complex nature of the AMR's, some of the key limiting factors that decide the acceptance of autonomous mobile robots in the manufacturing industry are in [4]:

1. Self-efficiency: It decides the ability of the user to adopt to new technology and perform given tasks under different circumstances. Some of the sub-factors include understanding the usage and application of AMR, ability to use the AMR without any assistance. It is highly necessary that human operator is well educated about the application of the AMR's so that upon interrupt, necessity suitable changes can be incorporated to the systems without bringing the whole production to a standstill.

2. Performance expectancy: Since the AMR comprises of many sensitive electronic components, the reliability of the overall system and the performance

of the said system will dictate the productivity in the usage of AMR's in the industry. Further due to the lack of regular maintenance schedule will bring down the performance expectancy of the robot.

3. Perceived risks: AMR's are prone to a traffic collision due to hardware failure, software failure which will often lead to improper material handling, thereby creating a scene of uncertainty towards performance and productivity. Such incidents usually end with a financial loss to the manufacturers.

4. Intentions to use: Intention of the use of AMR's is governed by users and the end application. If the technology is used as per the purpose of its creation then it will lead to easing out of work, thereby boosting the industries. Due to the software functionality of the AMR's once if the steps involved in the manufacturing process is trained, it will retain these steps thereby reducing the intensity of the work.

5. Privacy: Breach of private information through hacking of the software used will lead to wrong marketing, scrutiny, etc. vehicle to vehicle communication will involve transferring of vehicular data in order to have better productivity but however leads to breach of privacy. So, privacy of data will be important in the autonomous environment to ensure that the data generated by the systems will not get into the wrong hands.

6. Reliability: The reliability of the AMR's will mainly depend on the following factors: precision, accuracy, safety, security. Some of the sub-factors include getting confused due to extenuating circumstances of the everchanging needs of the warehouse, precision and the accuracy with which the system responds to the changing needs of a manufacturing industry, mean time between failure.

Further there are other constraints that limit the overall performance of the AMR's in the factory setup in [7]:

1. Getting the software correct so that the robot can navigate the factory setup autonomously and do the complex tasks in an efficient way.

2. Gathering enough real-world data so that the robot can accommodate the real-world changes in the factory setup.

3. Creating precise motion control so that the robot can maneuver in tight spaces and material handling is done in an efficient way.

4. Reducing the false positives that may occur by training the robot in enough real-world scenarios and distinguishing the data obtained between the actual data and the false positive ones.

5. Present Solutions Used for Autonomous Navigation in Factory Set-Up.

One of the evident problems that may be seen while using an AMR is the process of motion planning for an unstructured environment like a warehouse where there are continuous upgrades of the warehouse technology and thereby will be constant updating of the maps. In such a scenario where the start and the finish points are fixed, the motion planning will be complex. There are infinite possibilities for achieving the trajectory for a given start and finish. The best way would be to use a probabilistic approach to generate the trajectory using the concept of least action. The concept of least action will use the simple fact that the best possible path out of the infinite possible paths from a start point to the finish point would be the one that consumes the least energy in [8]. The principle of least action will generate a best possible path out of the infinite possibilities that are available from starting point to finish point considering all of the infinite paths that are possible. While using the concept of least action all of the possible paths are discretized for a small interval that is decided by the user, and the trajectory generated for this discretized instant for all the paths will be a straight line as shown in the **Figure 2** that is selected in [9].

To find the energy of each of the infinite path that is essential in the computation of the least action, there will be a Lagrangian that is defined for all the paths that will be a function of time in [8]. Further an action function is defined, which will be an integral of the Lagrangian for the path from start to the finish.as per the Eq. 1. The main objective would be to minimize this function, so that the best optimal path is generated.

$$S = \int_{ti}^{tf} L\, dT \tag{1}$$

where S = the action function that is defined for a given start and finish.

L = Lagrangian that is defined over the path which is the difference of the kinetic and the potential energy and is the function of the time.

ti = start time.

tf = finish time.

The Lagrangian for the system is defined as

$$L(x,\dot{x}) = K(\dot{x}) - P(x) \tag{2}$$

where $k(\dot{x})$ = overall Kinetic energy for the path.

P(x) = overall Potential energy for the path.

The physical significance of the action function would be that, the function would eliminate the infinite path which is not practical and will keep only the paths that make sense, from where the optimal path is selected. Further by discretizing the path for small instants can be useful for the process of real time obstacle detection in the environment and generating a trajectory that can be obstacle free. The path taken by the system that is generated through the concept of least action will give the complete history of the path that is taken to achieve the required goal which means that path taken by the robot is dependent on the path that the robot has taken

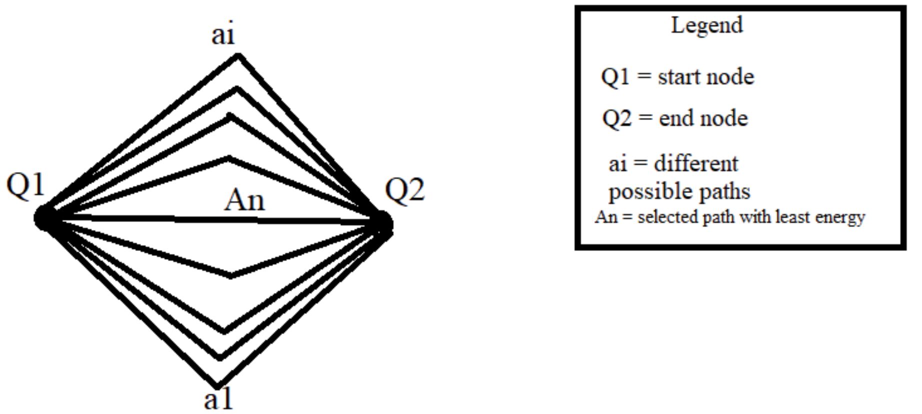

Figure 2.
Infinite possible paths that are possible for a given start and finish.

previously. The simplicity of this approach makes it more useful in using the proposed method in complex environments. So, the institute looks at incorporating the concept of least action for the motion planning of autonomous mobile robots that is developed at the common engineering facility center. The technology developed at the common engineering facility center is discussed in the paragraphs below.

The present solutions those are developed by the industry keeping in mind the different problems like the software complexity, performance, flexibility in the harsh conditions of a warehouse environment are as follows in [10, 11]:

1. Goods to person picking robots: companies like IAM, robotics, gray orange and blue offer mobile robot solutions that are loaded with modern technology and add new efficiency to the tasks done in factory setup. These robots can be programmed to have flexible routes in the factory set-up and requires less infrastructure to set up. The computer interface is friendly and easy to understand. Thereby the human machine interaction happens in a smooth way.

2. Self-driving forklift: Linde's new automated forklift consists of navigation lasers, 3D camera and visual and acoustic warning indicator that enables to move safely around human workers. The company also includes the feature of detection of real-time obstacles and adjust suitably. These things can work in fleet thereby optimizing the performance of the warehouses. These are being used in Kerala, Gujarat, Madhya Pradesh for different industries like electronics, consumer. The system further is mainly used as an artificial intelligence solution to the said product and has been installed in the manufacturing setup at ITC.

3. Autonomous inventory robots: FETCH's tag surveyor consists of three RFID mounted for optimal coverage and has reliability and consistently detect the products up to 25 feet away, thereby reducing the manual inventory count. Typically, the initial cost for such robots will be high due to complexity of the system. However, the run time costs will be reduced as the labor required to do the inventory will be reduced. This technology is in research stages currently in India and companies like iFuture robotics are at the forefront to develop a cost-effective solution.

4. Amazon air prime: This is the advanced delivery system developed by AMAZON that is used to deliver the products to customers through the means of UAV's. The drones usually make their way through automated tracks and lift on to open sky and autonomously deliver to the customers. This was first implemented in 2016 in the UK and based on the success the company looks to expand the trial on a larger scale.

5. Robomart: It is a self- driving store that focuses on transferring of goods that are pre bought online. Robomart is designed to be completely autonomous but also has the additional feature of being completely electric.

Some of the current solutions that are incorporated in IISC's smart manufacturing CEFC facility are shown in the **Figures 3**–**5**.

Figure 3 shows the robot arm that is used to distinguish and sort things from the conveyor. The robot has an interactive human machine interface through which suitable instruction to the robot can be provided. The instructions provided are codes that can be suitably uploaded to the interface. Further the stabilizer provided to the robot arm will ensure the smooth operation of the robot. **Figures 4** and **5** shows the

Figure 3.
Yasakawa Robotic arm used for to pick and sort different items from a conveyor.

Figure 4.
Autonomous mobile vehicle/Hanhwa Cobot.

autonomous robot used for material handling process throughout the factory setup. There magnetic tapes that are provided along the floor of the smart factory which will guide the robot through the different parts of the factory. Further the robot is provided with obstacle detection system that will simply stop if the robot senses an obstacle along the path of motion. Further to ensure the safety of the human

Figure 5.
Autonomous mobile vehicle/Hanhwa Cobot system collaborating with robotic arm for material handling process.

operators there are emergency brakes that are provided to the system. The motion path for the robot can be suitably programmed according to the requirements and can be uploaded to the interactive human machine interface.

7. Conclusion

The growth of any country is dependent on the investments that the country makes in the manufacturing and the technological upgrade. This report deals with how the technology, the advent of Industry 4.0, and demands of the Indian market make India a viable choice. There are many viable entities like China, which act as a main competitor by the fact that it spends around 53% of the GDP in the manufacturing. There is a high level of foreign direct investment that the government of China has encouraged to improve the manufacturing and warehousing scenarios. However, there are certain limitations like the lack of good infrastructure for the manufacturing industry, IPR violations, etc. that the industries face making China not a viable option for companies to look at. In such a scenario, the Indian markets emerge as a suitable alternative where the service sector accounts to high amount of the overall GDP of the country at around 53% in [12]. Additionally, the affordability of the technology, the initiative taken by the Indian government makes it a suitable alternative for the companies to look at. Further concept of IOT is looked at as an important factor and is expected to capture close to 20% of the overall IOT share of the globe. Government of India looks at the initiatives of green corridor, setting up of isolated warehousing environments and make in India initiative encourages company to setup shops in India. Due to these initiatives India looks at leapfrogging the world's major players like China, Germany, USA as a major technological player for the industries to look at. Further for any industry to succeed the labor has to be skilled which India has in abundance. This report looks at the different concepts that may affect a typical warehousing scenario and how it affects the overall performance. Human machine interaction will play an important factor in determining the efficiency of the process. Further as a prospective solution the concept of least action is proposed where there is an optimal solution from the infinite paths. The proposed theory is simple and can be used for real time obstacle detection for a complex environment. The proposed concept can be looked at for a multi-robot system and IOT can be used for better control of the proposed robotic system in the warehouse.

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