Chapter

Decision Support Models for the Selection of Production Strategies in the Paradigm of Digital Manufacturing, Based on Technologies, Costs and Productivity Levels

Joaquim Minguella-Canela and Irene Buj Corral

Abstract

Digital manufacturing has opened a new window in the way to approach the manufacture of parts. The possible switch from manufacturing and holding physical stock to manoeuvring with a fully-digital one is promising but still has not been undertaken-or only in a small proportion-by the majority of the manufacturing companies. What are the cost and productivity frontiers that halt the transformation taking place so far? When does it make sense, in terms of production volume and costs, to undertake this transformation? What level of savings could be achieved and what investments would be favourable? The base line of the present chapter is to depict quantitative tools to address the potential impact of endeavouring digital transformation in manufacturing environments, considering costing and production variables, as well as technological decision-making parameters. Keeping the modelling of the demand very basic, some exploration on the degree of postponement of the production is discussed. Also, decision support systems (DSSs) for manufacturing selection are reviewed. Finally, a case study serves to apply the mathematical framework presented and to quantify the results in a realistic industrial case. Using this case, the chapter outlines and describes how to apply artificial intelligence (AI) techniques to implement the DSSs.

Keywords: productivity, digital transformation, digital manufacturing, costs, decision support systems, decision support models, 3D printing, machining, injection moulding

1. Introduction

The industrial reality nowadays is as open that, in order to manufacture a certain part, there are usually many different alternative processes. However, the different viable alternatives may imply different cost schemes, and so, the decision on which process should be selected may not be such straightforward but linked to the values of several parameters of both the processes and the demanded part(s).

Building on this basis, in most cases, there is not a single solution of manufacturing that is optimal in all cases, and the objective of the present chapter is to provide the necessary guidelines to facilitate the decision-taking when selecting from different manufacturing processes.

Starting with the depiction of a general cost scheme, the chapter provides a useful modelling artefact to be able to tackle questions such as the following:

- What process should be used to manufacture a certain batch of a specific part?
- What process should be used to manufacture a certain series of a specific part?
- What manufacturing costs will be incurred if a certain manufacturing process is selected?
- When will it be economically favourable to undertake a certain investment to optimise an existing manufacturing process to obtain a specific product?
- When will it be economically favourable to undertake a certain investment in a new manufacturing process in order to start the manufacturing to obtain a specific product?

Having defined what is optimal concerning the costs' modelling, the present chapter also wants to bring some attention to the effect of manufacturing strategies imposed from the demand side. More and more frequently, the variability and uncertainty in the demand tend to force the production paces, for example, switching from manufacturing-to-stock (MTS) to engineering-to-order (ETO) paradigms. This is approached in the literature as the *level of postponement* of the manufacturing operation and has an effect in the manufacturing and stocking costs, which is also addressed in the present chapter.

Postponement in manufacturing has an important double-edged consequence. On one end, in order to be able to defer some (or all of the) production stages, it is important to embrace the digital stocking of the parts. On the other end, tooling should be avoided, bearing in mind that flexibility is key to achieve a fast response capability.

Following these considerations, the present chapter also reviews and comments on some *artificial intelligence* approaches in the form of decision support systems (DSS) in order to fulfil the decision-taking when aiming at selecting the most favourable manufacturing processes for a certain part. Indeed, the final decision on the manufacturing strategy to be embarked will have to be taken based on (i) technology capabilities, (ii) production organisation constraints and (iii) market-demand orientation. For this reason, to achieve the best decision-taking, the entire mathematical framework presented will have to be combined with in-depth technological knowledge and the most appropriate market approach.

Finally, the chapter illustrates the decision-taking and results in a case study that serves to illustrate the opportunity to shift to digital manufacturing technologies. The case study starts analysing the cost levels and equilibrium point for shifting from a very rigid (traditional) manufacturing technology to a more flexible one (3D printing). Finally, the case study deals with the limits on the possible benefits yielded by the product optimisation in a digital perspective, looking at what results could enhance for further improved production results.

2. Modelling framework: costing levels per technology

Modelling the cost framework of a specific process is crucial in order to take proper decisions on which process to select among the several available choices. However, by the same token, it is important to utilise the most well-fitting models in order to be able to take accurate decisions. It is also important to handle models as simplest as possible in order to avoid being stuck in a process parameter-evaluation stage.

One of the most applicable cost structures that can be found in literature is the model formulated by Hopkinson and Dickens [1]. This model was elaborated to be applied to 3D printing manufacturing technologies but, in particular, can be applied to any manufacturing technology in which the energy consumption costs of the machines are negligible in comparison to the rest of the costs in the model (i.e., if the energy-associated costs account for less than 1% of the final total cost).

In this chapter, the cost framework presented as a general cost model will be a very broad (traditional) one. The idea is to elaborate a simple and incremental costing model that can be further complicated by the reader, but that, at the same time, can be kept simple to facilitate its use with little parameterisation information.

In addition, the assumptions and simplifications will be made inside the model-and so they could be reverted by the reader if necessary.

2.1 General model

One general cost model, simple and broad enough to model the total costs in monetary units per year (m.u./year) incurred by the operations associated to manufacturing and keeping the manufactured parts in stock, is the one presented in Eq. (1):

$$Ct\left[\frac{m.u.}{year}\right] = Cp + Cs + Ci + Cr \tag{1}$$

where *Ct* is the total annual cost of manufacturing and keeping in stock the number of annual desired units (m.u./year); *Cp* is the total annual cost of the preparation of the production of batches in order to manufacture the desired number of units (m.u./year); *Cs* is the total annual cost to keep in stock the necessary parts to properly serve the desired number of units (m.u./year); *Ci* is the total annual cost of investments needed in the specific manufacturing system (m.u./year); *Cr* is the total annual cost caused by the rest of the factors independent from the lot or series size in order to manufacture the number of desired parts (m.u./year).

At this point, it is important to mention that this general model does not address additional costs generated in the entire product value chain than those strictly concerning the manufacturing and stocking in the production premises. For example, the costs of shipping the products across the globe as well as some costs associated to the inventory in the long term (obsolescence, spoilage, etc.) are not to be included within the factors declared in Eq. (1). Concerning this, some specific comments will be added when introducing the issues of production postponement in upcoming sections.

Then, starting from this very general model, it is possible to make some assumptions that are ordinary and that, at the same time, facilitate the evaluation of the associated costs. Specifically, the following is assumed:

- The demand stays constant throughout the year.
- The stock of parts is emptied linearly.
- The production is synchronised with the demand, so that the warehouse is filled again just when the corresponding stock is finished.

These assumptions regarding stocks can be summarised graphically as shown in **Figure 1**. As it can be seen, the average level of stocks throughout the year corresponds to B/2 (*B* being the size of the batches to be manufactured) and the number of annual preparations is equal to *D/B* (*D* being the annual demand of parts to be manufactured).

Accepting these assumptions, the *cost of the preparations* for the production process *Cp* can be calculated as indicated in Eq. (2):

$$Cp\left[\frac{m.u.}{year}\right] = \frac{D}{B} \cdot Tp \cdot Chp \tag{2}$$

where *Cp* is the total annual cost of the preparations of the production batches in order to manufacture the desired number of parts (m.u./year); *D* is the annual demand of parts to be manufactured (number of parts); *B* is the batch size to make (number of parts); *Tp* is the preparation time of the corresponding process (h); *Chp* is the cost of the time of preparing the corresponding process (m.u./h).

And the *cost of the stocks Cs* can be calculated as indicated in Eq. (3):

$$Cs\left[\frac{m.u.}{year}\right] = \frac{B}{2} \cdot Csp \tag{3}$$

where *Cs* is the total annual cost incurred to keep the necessary pieces in stock in order to properly serve the desired number of pieces (m.u./year); *B* is the batch size to manufacture (number of parts); and *Csp* is the cost of keeping a part in stock for a year (m.u./part_year).

On the other hand, assuming that investments are amortised in a number of years *y*, the *costs of annual investment Ci* can be calculated as indicated in Eq. (4):

$$Ci\left[\frac{m.u.}{year}\right] = \frac{Cet}{y} \tag{4}$$

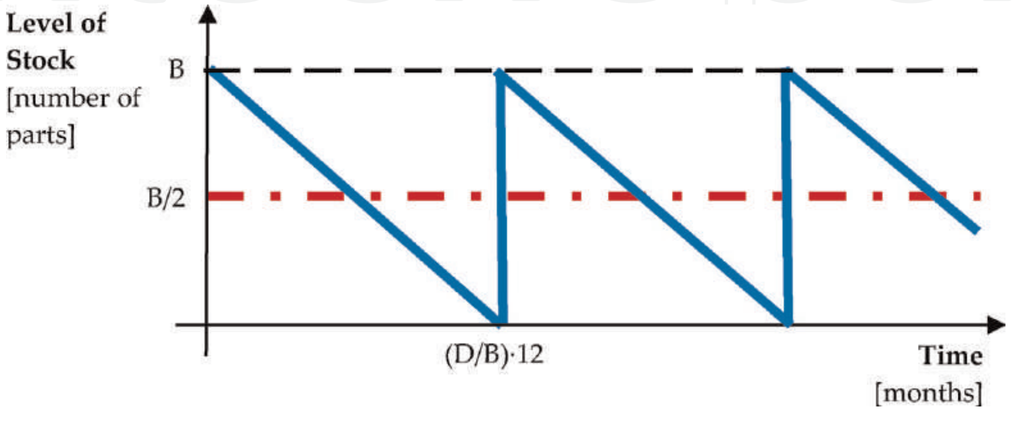

Figure 1.
Evolution of stock levels taking into account the considerations set on the inventory policy. B is the size of the batches to be manufactured and D is the total annual demand, both expressed in number of parts.

where *Ci* is the total annual cost incurred in investments for the manufacturing system (m.u./year); *Cet* is the total cost incurred in equipment and tooling for the manufacturing system (m.u.); and *y* is the timespan in which it is decided to amortise the tooling and equipment required (years).

Finally, there are other manufacturing costs, which are associated, among others, with the costs of raw materials and the costs derived strictly from manufacturing cycle times. Assuming that those costs are all proportional to the number of parts manufactured, the *rest of the costs Cr* can be calculated as indicated in Eq. (5):

$$Cr\left[\frac{m.u.}{year}\right] = D \cdot Cd \tag{5}$$

Where *Cr* is the total annual cost caused by the rest of the factors independent of the size of lot or series to make the number of desired pieces (m.u./year); *D* is the annual demand for parts to be manufactured (number of parts); and *Cd* is the direct cost per part caused by the rest of the factors independent of the size of lot or series (m.u./year).

In this way, the general model of production costs presented in Eq. (1) can be further detailed as the one described in Eq. (6):

$$Ct\left[\frac{m.u.}{year}\right] = \frac{D}{B} \cdot Tp \cdot Chp + \frac{B}{2} \cdot Csp + \frac{Cet}{y} + D \cdot Cd \tag{6}$$

Concerning the scope of this model, again, it is worth mentioning that the general model deployed in Eq. (6) does not approach the entire product value chain, but only the manufacturing and holding in the production premises.

Concerning the level of detail of the fundamental factors, it is also interesting to visit some other models in the literature, which introduce more parameters in the calculation of such factors. For example, the addition of a parameter for accounting an additional amount of money to ensure a proper treatment of perishable goods can be found. Moreover, the costs of warehousing management or even the cost of capital is usually considered within the stock cost calculation, although some authors advocate maintaining it as a separate cost factor [2]. Indeed, the costs generated by the stocks and their management have a huge effect on the manufacturing decision-taking and are at the grounds of the *lean manufacturing* approaches.

Because of this, other authors incorporate a special treatment to the demand, modelling it as a probability distribution function [3], which leads to results that are more accurate and opens the door to multi-scenario analysis, yet implying a much more complicated decision models than the general model discussed in the present chapter.

2.2 Determination of the optimal batch and its associated manufacturing costs

2.2.1 Size of the optimum manufacturing batch B^*

Starting from a cost model such as the one presented in the previous section (Eq. (6)), which takes into account the costs of preparation, manufacturing, amortisation of investments and also holding parts in the factory stock, it can be determined which batch size will minimise the total cost (i.e., the optimal batch B^*) as follows (Eqs. (7), (8) and (9)).

$$\frac{dCt}{dB} = \frac{0 \cdot B - 1 \cdot D \cdot Tp \cdot Chp}{B^2} + \frac{1}{2} \cdot Cs + 0 + 0 = 0 \tag{7}$$

$$\frac{D \cdot Tp \cdot Chp}{B^2} = \frac{Cs}{2} \Leftrightarrow \tag{8}$$

$$B^* = \sqrt{\frac{2 \cdot Tp \cdot Chp \cdot D}{Cs}} \tag{9}$$

Eq. (9) is coherent with the experience in manufacturing. The number of parts in an optimal batch B^* holds direct relation with the preparation time Tp, the preparation cost Cp and the total number of units to make D. The higher the values of these parameters, the bigger the value of the optimal batch size associated with its manufacture. On the other hand, the optimal batch size B^* has a reverse proportionality ratio with the cost Cs of keeping a part in the stock. Indeed, the more expensive it is to have a part in stock, the more favourable it will be to adopt manufacturing strategies based on small batches.

In fact, it is interesting to note that, based on the second derivative of the cost scheme presented in Eq. (6), it can be stated that this optimum point will always be a minimum for the total costs. This is because the values of D, Tp and B will always be positive numbers and, therefore, the value of the second derivative (Eq. (10)) will always be positive for any value of these variables.

$$\frac{d^2Ct}{dB^2} = \frac{0 \cdot B^2 - (2B \cdot (-D \cdot Tp \cdot Chp))}{B^4} + 0 = \frac{2 \cdot D \cdot Tp \cdot Chp}{B^3} > 0 \,\forall D, Tp, B \tag{10}$$

2.2.2 Costs in the optimum manufacturing batch C*

Starting from a cost model such as that obtained in Eq. (6), using the expression corresponding to the optimal batch B^* calculated in the previous section, the following is obtained:

$$Ct_{(if\ \ B=B^*)}\left[\frac{m.u.}{year}\right] = \frac{D}{\sqrt{\frac{2 \cdot Tp \cdot Chp \cdot D}{Cs}}} \cdot Tp \cdot Chp + \frac{\sqrt{\frac{2 \cdot Tp \cdot Chp \cdot D}{Cs}}}{2} \cdot Cs + \frac{Cet}{y} + D \cdot Cd \tag{11}$$

which, grouping terms, can be formulated as:

$$Ct_{(if\ \ B=B^*)}\left[\frac{m.u.}{year}\right] = \sqrt{2 \cdot D \cdot Tp \cdot Chp \cdot Cs} + \frac{Cet}{y} + D \cdot Cd \tag{12}$$

In some cases, it is not necessary to use specific tooling or take into account the amortisation costs of the equipment. For example, this can happen in case a manufacturing process without specific tooling (*a flexible process*) is used, and, at the same time, it has a very low cost of equipment in relation to its repayment period. If this is the case, the calculation of the total costs is further simplified, as it is presented in Eq. (13):

$$Ct_{(if\ \ B=B^*,\quad Cet=0\ )}\left[\frac{m.u.}{year}\right] = \sqrt{2 \cdot D \cdot Tp \cdot Chp \cdot Cs} + D \cdot Cd \tag{13}$$

In any of these cost descriptions, it can be seen that, when working on the production of different parts requiring continuous production changes, reducing the preparation time will have a much greater effect on the total costs than it could seem at the very first glance.

2.3 Specific models for specific manufacturing technologies: 3D printing, machining and injection moulding

Disregarding the general costing model presented in the previous sections, which is powerful because of its generality, the manufacturing cost levels for specific manufacturing technologies can also be determined in an approximate manner by means of the most relevant cost factors in that certain technology.

For example, in 3D printing technologies, the cost factors that are the most important descriptors and that can be characterised relating to them are [4]: (i) part weight, (ii) part dimensions and (iii) construction time. In some works (e.g., see [5]), the cost modelling in the case of 3D printing technologies has been formulated as the function of the following factors: machinery costs, materials costs, energy consumption costs and labour costs. In any case, digging again in the method to obtain those terms, it is possible to find that the fundamental factors of mass z dimension and construction times correlate with the indicated (i) part weight, (ii) part dimensions and (iii) construction time.

Taking the simplification modelling to a further stage, there have been some recent attempts to construct and validate useful specific and simplified cost models, for example for 3D Printing, machining and injection moulding manufacturing technologies [6]. In this case, the results were found of relevance for 3D printing and machining, while the fit was not appropriate for the injection moulding technologies.

3. Manufacturing context: critical batches and critical series vs. ultrapostponement strategies

3.1 Critical batch

Given two processes A and B that allow to obtain the same part P, A being a process that requires the use of specific tooling and B a process that does not require them, the critical batch Bc is the one that implies the same productivity in time per manufactured part (that is, $T_A = T_B$).

Indeed, the manufacturing time per part in the case of a tooling process (T_A), assuming that it involves a process preparation time different than zero minutes ($Tp_A \neq 0$), can be determined as presented in Eq. (14):

$$T_A\left[\frac{min}{part}\right] = \frac{Tp_A}{B_A} + Tf_A = \frac{Tp_A + Tf_A \cdot B_A}{B_A} \tag{14}$$

where T_A is the manufacturing time per part in the case of an A process with tooling (min/part); Tp_A is the machine preparation time of the A process (min)*;* Tf_A is the time of individual forming of a part using the process A (min/part); and B_A is the size of the batch to be manufactured using the A process (number of parts).

On the other hand, the manufacturing time per part in the case of a process without tooling (T_B), in which it is considered that the machine preparation time is null ($Tp_B = 0$), results as follows (Eq. (15)):

$$T_B\left[\frac{min}{part}\right] = \frac{Tp_B}{B_B} + Tf_B = Tf_B \tag{15}$$

where T_B is the manufacturing time per part in the case of a B process without tooling (min/part); TfB is the machine preparation time of the B process (min); TcB

is the time of individual forming of a part using the *B* process (min/part); and L_B is the size of the batch to be manufactured using the *B* process (min).

As can be seen, the fundamental reason for varying the cost schemes of two manufacturing processes such as the ones presented here is the effect of the preparation time *Tp* of the process (sometimes also called machine preparation time) on the manufacturing time T_B. In case this is not equal to zero, its impact will have to be taken into account in the determination of manufacturing time per unit produced. In this sense, the existence of non-zero machine preparation time will especially penalise the production of parts in small batches, accounting for a most diluted effect in the case of large batches.

In this way, regarding the determination of the critical batch *Bc*, it is important to emphasise that what will have effect is not the existence of some or other specific tooling, but the temporary impact of the preparation. Once the part is finished, such preparation is required to switch all the necessary and start making a different part.

Graphically, this behaviour is illustrated in **Figure 2**. The individual forming times of the *A* process (with tooling) are affected by the machine preparation time. As the batch size increases, manufacturing costs per part produced are reduced asymptotically with a horizontal limit Tf_A. Since the individual conformation times for the *B* process are constant and always equal to Tf_B, whenever Tf_A is less than Tf_B, there will be a cut-off point between T_A and T_B, which is called equilibrium point. The equilibrium point marks the critical batch (*Bc*) between processes *A* and *B*.

In the case referred here, for batches with number of units lower than the number of parts corresponding to *Bc*, it will be more productive to use the process without specific tooling *B*, since Tf_B will be equal to T_B. Instead, for cases where the number of units to be used as the working batch *B* is greater than *Bc*, the process with specific tooling *A* will be more productive.

As a practical detail, it should be noted that, given the way in which it is obtained, the equilibrium point can be any positive number, in particular, not necessarily a whole number. In the case of manufacturing in discrete processes, however, it should be noted that it is necessary to work with natural numbers of parts, as it would make no physical sense to manufacture decimal parts of products.

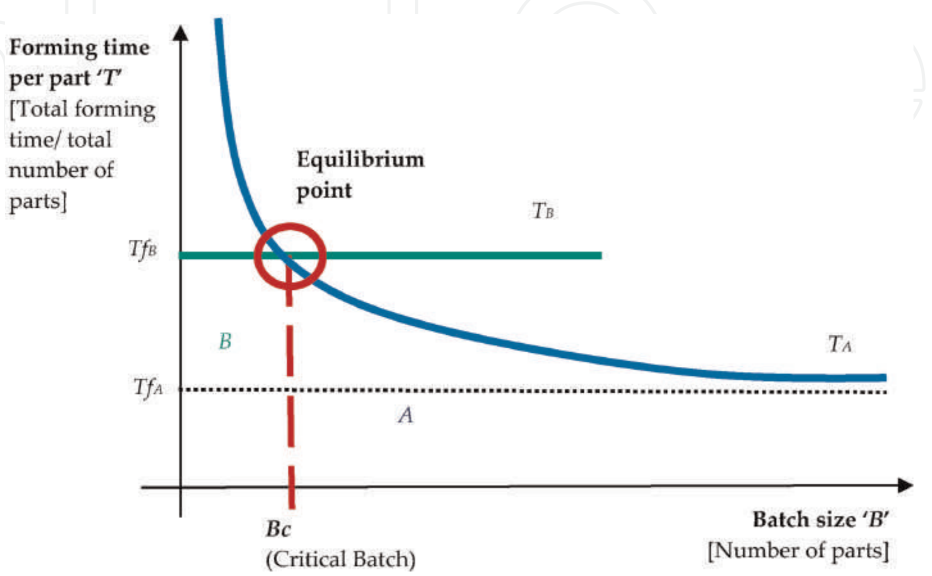

Figure 2.
Forming time per part as function of the batch size for different processes (A process with tooling-rigid process-and B process not requiring a specific tooling-more flexible process.)

For these cases, the immediately lower integer will be set as the upper limit of the number of units that make the *B* process more productive. Also, the immediately superior integer number will be set as the lower limit of the number of units which makes the process *A* more productive to obtain the product.

In case the size of the critical batch is a natural number, this number will be set as the upper limit of the number of units that make the *B* process more productive, since it will always be easier to work without the need for specific tooling.

3.2 Critical series

Suppose once again two processes *A* and *B* that allow obtaining the same part *P*. Given the two processes, it is called *critical series Sc*-the one that implies the same level of total costs for both processes (i.e., $C_A = C_B$).

In some cases, it will be possible to maintain the assumptions made in the previous section; namely supposing *A* a process that requires the use of specific tooling (a rigid process) and *B* a process that does not require it (a fully flexible process). However, many times these assumptions will not be straightforward when a process is assessed in the long run. This is due to the fact that all processes require some tooling and equipment, which can have a negligible impact on a very short batch manufacturing. Nevertheless, its amortisation cost has to be necessarily taken into account when setting its cost scheme and comparing it with other possible options.

On the other hand, many different discrete manufacturing processes, which are batch processes that obtain parts, work discontinuously with a maximum number of parts that can be manufactured in a single run and that cannot be exceeded. For example, this occurs in processes where parts are manufactured in green but require a subsequent thermal treatment in which the whole lot enters a non-continuous furnace at a time. It would also be a sample of this case: the manufacture of parts by means of 3D printing in a bed or in a building platform. These types of 3D printing manufacturing processes determine the maximum size of the batch to be manufactured from the available contact surface with the bed or the maximum mass volume available on the platform. Therefore, the selection of the manufacturing working batch cannot be done minimising the costs of a single function but will have separate cost functions depending on the number of production runs to be set in a demanded batch.

For this reason, in a general case, it is advised to determine the *critical series Sc* using the general cost model presented in Eq. (1) and replacing the demand *D* by the *critical series Sc*. In this way, as shown below, the expressions given are Eqs. (16)–(20):

$$Ct_A = Ct_B \Longleftrightarrow \tag{16}$$

$$Cp_A + Cs_A + Ci_A + Cr_A = Cp_B + Cs_B + Ci_B + Cr_B; \tag{17}$$

$$\begin{aligned} &\frac{Sc}{B_A} \cdot Tp_A \cdot Chp_A + \frac{B_A}{2} \cdot Cs_A + \frac{Cet_A}{y_A} + Sc \cdot Cd_A \\ &\quad = \frac{Sc}{B_B} \cdot Tp_B \cdot Chp_B + \frac{B_B}{2} \cdot Cs_B + \frac{Cet_B}{y_B} + Sc \cdot Cd_B; \end{aligned} \tag{18}$$

$$\begin{aligned} &Sc \cdot \left(\frac{Tp_A \cdot Chp_A}{B_A} + Cd_A \right) + \frac{B_A}{2} \cdot Cs_A + \frac{Cet_A}{y_A} \\ &\quad = Sc \cdot \left(\frac{Tp_B \cdot Chp_B}{B_B} + Cd_B \right) + \frac{B_B}{2} \cdot Cs_B + \frac{Cet_B}{y_B}; \end{aligned} \tag{19}$$

$$Sc = \frac{\left(\frac{B}{2} \cdot Cs_B + \frac{Cet_B}{y_B}\right) - \left(\frac{B_A}{2} \cdot Cs_A + \frac{Cet_A}{y_A}\right)}{\left(\frac{Tp_A \cdot Chp_A}{B_A} + Cd_A\right) - \left(\frac{Tp_B \cdot Chp_B}{B_B} + Cd_B\right)} \tag{20}$$

Depending on the values that the corresponding parameters included in Eq. (20) can take, there might be a cut-off point in the positive range of the number of parts to be produced. If this is the case, the crossing point between the two processes compared will be again referred as the *equilibrium point* and will determine the size of the critical series *Sc*.

This situation is described in **Figure 3**, which shows the total manufacturing costs as function of the size of the manufactured series for two different processes *A* and *B*. As assumed along this section, the use of tooling and equipment cannot be neglected in the cost calculation of neither process and has to be incorporated into the model. As it can be inferred from **Figure 3**, in the presented case, process *B* is contemplated to be more flexible than process *A*-*B* having lower equipment and tooling costs. Also, *A* presents lower costs per single forming, thus leading to the existence of an equilibrium point (*Sc*).

3.3 Ultrapostponement strategies

Nowadays, a large stake of the products that are sold to the general public is very complex combinations of parts that normally have numerous production stages. Regardless of what the specific technological aspects dictate to the optimal-economical or less time consuming-organisation of manufacturing, there is always a market effect that intervenes in the production strategies. Serving the demand *where* and *when* it is produced is even more complicated in the cases in which the demand is unstable and when the products sold are frequently customised to the specific customer demanding them.

Again, having a look at previous works, it is established as customer order decoupling point (CODP), the moment when the customer acquires the product [7]. The CODP marks just a moment in time, notwithstanding the product sold is finished, in an intermediate manufacturing stage or when its production process has not even started. However, the position of the CODP in the product value chain is important, as it is the milestone in which the product is effectively wanted by the

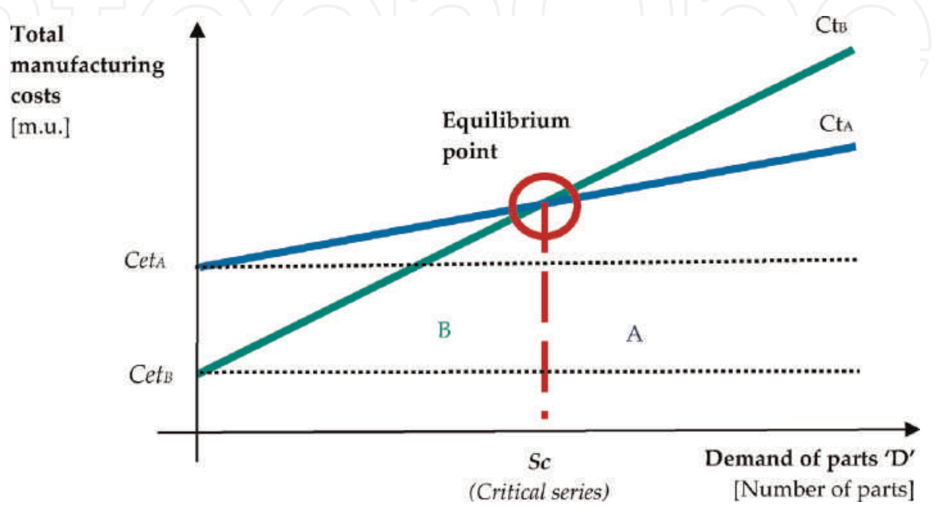

Figure 3.
Total manufacturing costs as function of the size of the series for two different processes A and B. In this case, the use of tooling and equipment is assessed in both processes, although process B is contemplated to be more flexible than process A.

customer, and it fixes the place in the product value chain where the so-called *postponement* effect occurs. The place where the postponement happens along the product value chain is referred as the *degree of postponement* of the production process.

Taking the postponement effect to one of its possible extreme positions, there is the possibility to operate in *pure-speculative* markets. These are, for example, the typical markets of regular alimentation products (i.e., yogurts, bread, bottles of water, etc.), which are goods that are produced and taken to the shops without any intervention of the customer in the production chain. In these production strategies, the selling side produces all the products in the quantities that match the selling expectations and just hopes that the demand will consume all the produced goods. Of course, these sorts of strategies are only adopted in markets with a very stable demand and with relatively low product costs. These strategies are also referred as make-to-stock (MTS) paradigms, as with them the production process works against the action of filling the product warehouse.

Moving then to the other possible extreme position, in some products, there exists the possibility of not even starting the design stage before the customer has effectively placed the order. These are considered the strategies of engineering-to-order (ETO) and are associated to products that must be completely customised to the customer, for example, a specific prosthesis for a health treatment or a bridge to be installed in a river. These sorts of strategies are common in markets with a very unstable demand (sometimes a demand that will only happen once in life) and with relatively high product costs.

Discussing a general case, as formulated by Yang et al. [8], moving upstream the CODP enhances the effectiveness and flexibility of the product supply chain. In effect, the ideal production process should only produce parts that it is sure that some customers will buy. However, in order to be capable of serving the demand in

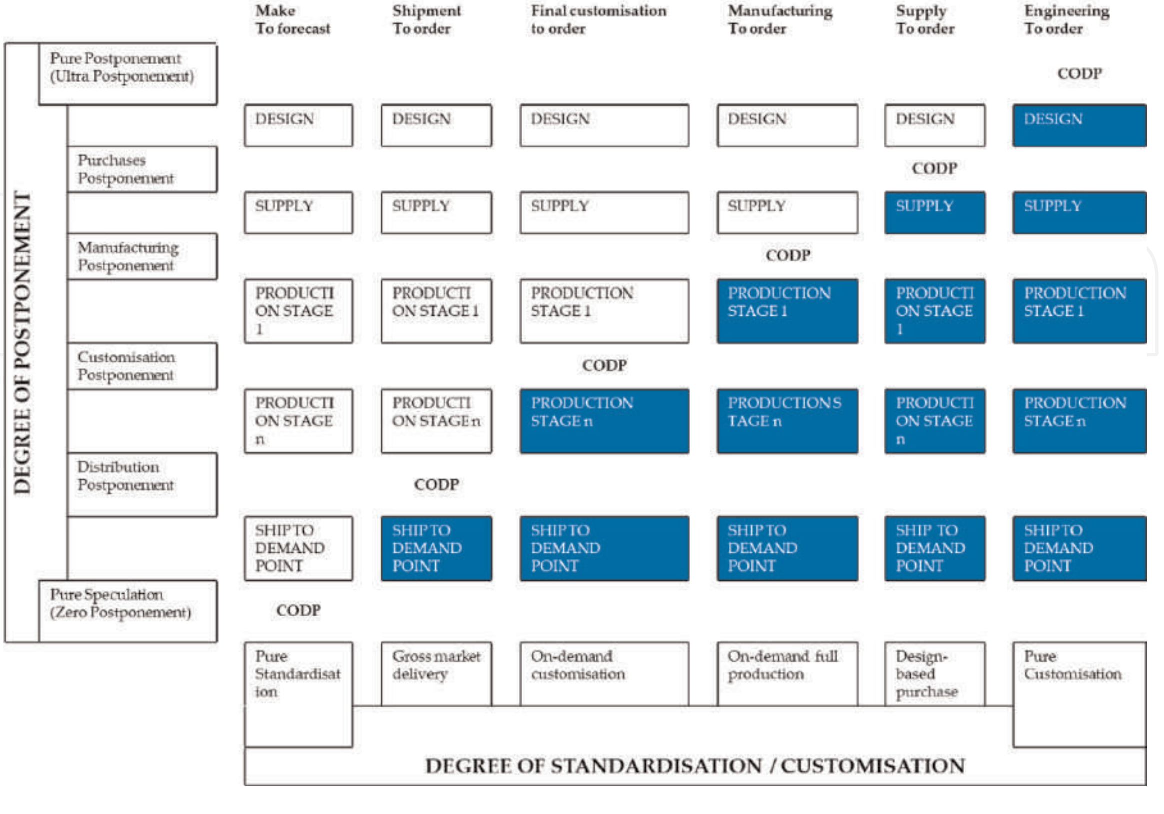

Figure 4.
Schematic representation of the CODP position in different situations along the value chain. Presented in [5] and elaborated from the findings of the study of Yang et al. [8].

the point and moment it is produced (*where* and *when*), some production processes may need to *start earlier* the manufacturing, as the product would not be ready if approached in a different manner.

The final strategy adopted, therefore, will have to be restricted due to many factors that could be grouped in: (i) technology capabilities, (ii) production organisation constraints and (iii) market-demand orientation. With all those constraints, it will be of interest to defer all the possible manufacturing stages. Some different levels of postponement that can be established as a product manufacturing policy are *make-to-forecast, ship-to-order, final customisation-to-order, manufacturing-to-order, supply-to-order* and *engineering-to-order* [5].

At this point, it will be key to be able to adopt digital manufacturing processes, more flexible than the traditional ones, which will imply lower manufacturing costs per part when addressing the forming of small batches of production. Having access to more and more flexible processes will make it viable to work economically and timely with nearly unitary batches of parts, thus allowing triggering the production only when the costumer has proceeded to pay for it.

Concerning to all this, **Figure 4** synthesises the many different possibilities on placing the CODP along the product value chain, and so the degree of postponement that could be associated to it: *pure-postponement (ultrapostponement), purchase postponement, manufacturing postponement, customisation postponement, distribution postponement and pure speculation (zero postponement).*

4. AI approaches for decision-taking: decision support systems (DSS)

The theoretical dissertation of computer systems to help in the decision-taking processes date as far as the late 1950s and early 1960s, probably being in the decade of the 1980s when it gained the most of its intensity. Regarding the interests in the present chapter, a decision support system (DSS) can be described in a general manner as a system capable of aiding the user to select the best option given the prospective results of the analysis of several scenarios. Curiously, it is interesting to know that the main authors have not agreed on a single definition of DSS and that, therefore, the their prescription may vary.

The common characteristics that described a DSS were enunciated by Alter [9]. Based on this description, DSS are specifically designed to facilitate the decision-making process but not on replacing the decision-taking role of the user. In addition, the DSS have to be fast in incorporating changes in the parameters and in producing new solutions in the new scenarios considered.

Some other authors stressed that the focus should be put on having systems containing both data and decision models [10]. In this sense, for a DSS, it is more important to optimise the effectiveness than the efficiency of the system.

Concerning taxonomy, Power [11] provided a classification of the DSS in 5 different categories depending on the assistance mode utilised by the system:

- Document-driven (DD-DSS): consisting of DSS based on the search and finding of the information in documentation

- Communication-driven (CD-DSS): consisting of DSS based on the communication between different users

- Data-driven or data-oriented (DO-DSS): consisting of DSS based on the utilisation of temporal data series

- Model-driven (MD-DSS): consisting of DSS based on statistical, financial models, being empirical, analytical or theoretical

- Knowledge-driven (KD-DSS): consisting of DSS based on the experience and knowledge in a particular area

Apart from the definition and categorisation, what is commonly agreed in the literature is what are the fundamental components of a DSS, namely: (i) the database or knowledge base, (ii) the model utilised-decision context and criteria rules- and (iii) the user-interface. Assuming that the decision-taking role is performed by the users, many authors agree that the users themselves are also a very important part in the system.

Concerning the level of interaction with the user, the DSS can be classified as passive, active or cooperative systems. Concerning the capability of interaction with the users, the DSS can be classified as single-user DSS and multi-user DSS.

4.1 Formal models and trends of DSS applied to manufacturing process selection

From the categorisation presented in the previous section, the majority of the DSS applied to manufacturing processes that can be found in the literature are KD-DSS. This may probably be since the decision taken in manufacturing technologies relies strongly on the experience and knowledge in the corresponding domain, and so the most ambitious experiences have been constructed over a nurtured manufacturing know-how database.

The selection of processes and process parameters encountered a research ignition with the emergence of the additive manufacturing technologies that took place during the late half of the 1980s. Following that, many research teams embarked on researching about consolidating the best possible advice for switching from one technology (normally a traditional manufacturing one) to a rapid (later considered additive) manufacturing technique.

In the 1990s, some authors completed a first model for yielding information about the election of additive manufacturing processes for applications of rapid prototyping (e.g., see [12, 13]). Since then, many AI-based advisory systems have focused on the manufacturing topics of *rapid prototyping*, *rapid tooling* and *rapid manufacturing* (e.g., see [14, 15]). Two outstanding achievements produced in the last 10 years at *Universitat Politècnica de Catalunya-BarcelonaTECH* are the *Rapid Manufacturing Advise System* (RMADS) proposed by Munguía in 2009 [16] and the *Design for Additive Manufacturing* (DFAM) for parts with high variability in the demand proposed by Morales in 2019 [17].

The RMADS software utilised a combination of several artificial intelligence (AI) techniques in order to deliver a concurrent and comprehensive concurrent engineering methodology to estimate the manufacturing costs and times comparing two different machines for selective laser sintering (SLS) technology. In Munguía's RMADS, expert systems were used, but also fuzzy logic, relational databases as well as neural networks. In comparison, the approach in Morales' DFAM system also utilised an expert system commanded by five layers of 'if-then' rules and a knowledge base. The system is prepared with information of the multi jet fusion (MJF) process and it also yields data on manufacturing costs that can be compared with injection moulding processes. However, the focus in this case is on assisting the 'non-expert' user on being able to redesign the parts-if needed-to better utilise the additive manufacturing (AM) capabilities.

Opening to the broad manufacturing advice, some solutions-the more specialised ones- focus only in providing technological advice on the process, material or even machine selection [18]. Some other solutions-much broader in content-take into consideration multiple manufacturing plants [19] or even the entire product value chain [20].

Concerning their architecture, most of the DSS incorporate expert systems based on rules for assessing the situations presented [21–23]. Some of the most recent ones also incorporate or assisted [17, 24, 25] machine learning procedures to enlarge its knowledge base during its operation. These later ones can be approached not only by a regular user but also by an expert that can feed the system with new knowledge on a continuous basis [26]. Some include fuzzy-logic learning features [15, 27].

As commented, some systems are intended to be proactive in the extension of its knowledge base. When not relying on the information directly provided by an external expert, the most utilised source of information reported by the academia is the link and download of on-line data that is finally incorporated in the knowledge base of the DSS [28–29].

Different to what is found in the literature for systems that manage and improve the performance of production lines, the self-learning capabilities that could be provided by the AI techniques have not been fully deployed in systems for decision-taking among different processes. In this sense, currently, the common use widely seen is the so-called hybrid intelligence learning use: the DSS is capable to produce a ranking or a statement on costs or other attributes [30]. However, the final decision-taking on the process and the follow-up and accumulation of new experiences still rely heavily on human operators.

The variables of study underlying the decision-taking are also diverse. Most of models use as parameters variables that evaluate economic and time aspects (i.e., costs and times), which are included at some point in almost every system developed. Many models incorporate technological rules and advise on manufacturing best practices [17, 23]. Finally, the newest models usually incorporate additional variables related to energy use [20], sustainability of the technology [31] and/or user-friendliness in order to build a balanced scorecard for decision-making.

Also, another trend that has been identified is the interest on providing advice on product design alternatives in the cases the system cannot derive a specific solution from the manufacturing processes database. Some recent contributions also give indications on complementary processes, such as those for post-processing and finishing the parts [32].

Being capable of yielding fully autonomous self-learning decision support systems is a paradigm that will only be able to be developed once advanced sensors would be fully deployed along the production means. Indeed, the deployment of self-learning sensor capabilities is currently in the strategic agendas and attracts the focus of research and development [33]. This achievement would lead to the materialisation of the so-called intelligent manufacturing systems (IMS) [34]. In this scenario, being in the Industry 4.0 era, the end users could gain access to collaborative services, having a more integrated human-machine interaction ecosystem, and the organisational, technical and decision-making levels could be synthesised at a unique level.

5. Case study application in an industrial product

Following what has been presented so far, most cases of application (products) will have the possibility to be manufactured by several (at least two) different production processes. Some of the processes will be more rigid and will usually lead

Order size	Machine preparation time of process *A*	Timely cost of preparing the corresponding process *A*	Cost of keeping a part in stock for a year	Cost caused by the rest of the factors independent of the series or batch size	Total cost incurred in new tooling for process *A*
D (parts/year)	Tp_A **(h/batch)**	Chp_A **(m.u./h)**	Cs_A **(m.u./part_year)**	Cd_A **(m.u./part)**	Ci_A **(m.u.)**
6000	2	30	2	0.15	6500

Table 1.
Size of the demand for the initial year, machine preparation time and different costs for the parts under initially planned process A.

to shorter forming times per unit (a priori) yet will imply higher costs in terms of tooling and batch preparation times that will have to be added to the forming times per unit.

Some other processes will be more flexible and will sometimes not require specific tooling, yielding smaller costs per produced part. However, the individual forming times per produced part will probably be higher than those in a more rigid production process, thus implying shorter production rates when the system achieves the stationary functioning.

With these two dissimilar choices (more rigid versus more flexible possible processes), the following application case tries to be useful to deploy the decision-taking framework that has been described along the chapter. The first part of the section concentrates on the characterisation of the available possibilities to manufacture the studied product and on determining the critical batches, total costs, costs per part and critical series for each of them. In this first part, the models presented are deployed as it must be done in a real application case, to compare cost levels and to quantify the outcomes of different levels of investment. Following that, the section recaps on how the DSS could be applied to this case and what structure could have to facilitate the user's decision.

5.1 Manufacturing of an accessory for an established product

A pharmaceutical company ordered to a workshop specialised on plastic the manufacture of a series of clip-type tweezers to add to one of its products: glucometers. With the incorporation of those tweezers, the product increases its added value a lot, yet the long run is not ensured with this first manufacturing order.

The initial planned manufacturing process is the injection of the plastic parts using steel moulds-an in-house technology already available in the production facility. The estimation of units, the preparation time and the different costs for the parts under initially planned process A is summarised in **Table 1**.

5.1.1 Size of the optimum manufacturing batch $B_A{}^*$ and total costs of process A (Ct_A)

The starting point about the manufacturing process to be adopted is to characterise the optimal manufacturing batch B^* and the total manufacturing costs Ct_A yielded by process A.

Assuming that in a year of production all the specific tooling has to be fully amortised and adopting the standard manufacturing cost model presented in the previous sections, $B_A{}^*$ and Ct_A can be calculated according to Eqs. (21) and (22):

$$B_A{}^* = \sqrt{\frac{2 \cdot Tp_A \cdot Chp \cdot D}{Cs}} = \sqrt{\frac{2 \cdot 2h \cdot 30\,\frac{m.u.}{h} \cdot 6000\,\frac{parts}{year}}{2\,\frac{m.u.}{year}}} = 600\,parts \tag{21}$$

$$\begin{aligned} Ct_A &= \frac{D}{B_A} \cdot Tp_A \cdot Chp + \frac{B_A}{2} \cdot Cs + Ci + D \cdot Cd_A \\ &= \frac{6000\,parts}{600\,parts} \cdot 2\,h \cdot 30\,\frac{m.u.}{h} + \frac{600\,parts}{2} \cdot 2\,\frac{€}{year} \\ &+ 6000\,parts \cdot 0,15\,\frac{m.u.}{part} + 6500\,m.u. = 8600\,m.u. \end{aligned} \tag{22}$$

Regarding the total cost of process A, it is important to stress that the injection moulding machine is considered an in-house technology with a very long period of amortisation. Therefore, the amortisation cost incurred for a very short run of production can be neglected in front of the other costs considered. In this regard, in case it should be taken into account, the costs of investment should be modified accordingly.

Within this context, the workshop has just introduced a new 3D printing technology, with which it is possible to manufacture the required parts without specific tooling. However, in this case, the parts must be manufactured in batches of 400 units. This technology is characterised by the time and costs summarised in **Table 2**, while the annual demand is considered to be the same.

5.1.2 Unit costs per part using each of the processes (A: injection, B: 3D printing)

In order to calculate the cost per part C_A for process A (injection moulding), it is possible to divide the result obtained in the previous section by the total number of parts to be manufactured:

$$C_A = \frac{CtA}{D} = \frac{8600\,m.u.}{6000\,parts} = 1.43\,\frac{m.u.}{part} \tag{23}$$

For process B (3D printing), using the general expression and taking into account that there is no specific tooling needed to be quantified, C_B can be obtained using the general costing model as follows (Eqs. (24) and (25)):

$$Ct_B = \frac{6000\,ud}{400\,ud} \cdot 1\,h \cdot 30\,\frac{€}{h} + \frac{400\,ud}{2} \cdot 2\,\frac{€}{\tilde{a}no} + 6000\,ud \cdot 2\,\frac{€}{ud} + 0 = 12850€ \tag{24}$$

Machine preparation time of process *B*	**Timely cost of preparing corresponding process *B***	**Batch size imposed by process *B***	**Cost of keeping a part in stock for a year**	**Cost caused by the rest of the factors independent of the series or batch size**
Tp_B **(h/batch)**	Chp_B **(m.u./h)**	B_B **(parts)**	Cs_B **(m.u./part_year)**	Cd_B **(m.u./part)**
1	30	400	2	2

Table 2.
Machine preparation time and different costs for the parts under possible alternative process B.

And with this result, the cost per manufactured part equals to:

$$C_B = \frac{CtB}{D} = \frac{12850\ m.u.}{6000\ parts} = 2.14\frac{m.u.}{part} \tag{25}$$

Again, in the calculation of the total costs for process B, it is assumed that the amortisation cost of the overall equipment can be neglected in front of the other costs considered. In case it should be taken into account, the costs of investment should be modified accordingly.

5.1.3 Critical series per part taking into account the two options (A: injection, B: 3D printing)

To calculate the critical series of the two possible processes, it is important to take into account that the working batches set are different. In process A, it is possible to work in the situation of the optimal manufacturing batch $B_A{}^*$ calculated in Section 5.1.1. However, in process B, the manufacturing batch is fixed to 400 parts in every run.

In this situation, the size of the critical series can be determined by simply defining as equal the two general cost models (Eq. (26)):

$$Ct_A = Ct_B \tag{26}$$

And, since process B has no additional tooling to be considered, Eqs. (27)–(29) can be applied:

$$\frac{D}{B_A}\cdot Tp_A\cdot Chp_A + \frac{B_A}{2}\cdot Cs_A + D\cdot Cd_A + Ci_A = \frac{D}{B_B}\cdot Tp_B\cdot Chp_B + \frac{B_B}{2}\cdot Cs_B + D\cdot Cd_B; \tag{27}$$

$$\begin{aligned}&\frac{D}{600}\cdot 2\,h\cdot 30\frac{m.u.}{h} + \frac{600\ parts}{2}\cdot 2\frac{m.u.}{year} + D\cdot 0,15\frac{m.u.}{part} + 6500€\\ &= \frac{D}{400}\cdot 1\,h\cdot 30\frac{m.u.}{h} + \frac{400\ m.u.}{2}\cdot 2\frac{m.u.}{year} + D\cdot 2\frac{m.u.}{part};\end{aligned} \tag{28}$$

$$D = \frac{6700}{1.825} = 3671.23\ ud \tag{29}$$

Therefore, if the total demand were to be 3671 parts or less, it would be better to implement process B (3D printing). On the contrary, in a scenario with a demand starting from 3672 parts and more, it would be better to use the A (injection) process.

As the current situation is that the annual demand is of 6000 parts to be produced, the advice for process undertaking is to manufacture the parts using process A, which will require a specific tooling, but will also yield a smaller cost per produced part.

5.1.4 Product optimisation with process B: 3D printing

Given the opportunity offered by 3D printing technologies to make better designs, and in view that the demand for parts can grow, it is interesting to study a scenario of product optimization through weight reduction and modification of non-critical geometries. This is a very common procedure in the product design iteration for 3D printing and it is commonly retrieved in the literature as design for additive manufacturing (DFAM). In the present case study, it would be assumed that the envelope dimensions of the part to be manufactured do not change during this process; and so that the manufacturing batch size remain constant as in the previous case (B_B = *400 parts*).

By undertaking those steps, it would be easy to decrease the cost per part yielded by process *B*. However, how much should the cost per part manufactured by process *B* be reduced to achieve a situation in which the critical series is 10,000 parts per year?

To determine the maximum costs of process *B* in the case of a critical series equal to 10,000 units, the same expression as in the previous section can be utilised. Nevertheless, this time it is necessary to isolate the costs independently of the batch size for the "C_C" process (being *C* the process of 3D printing the optimised product), as it is done in Eqs. (30)–(32).

$$\frac{D}{B_A} \cdot Tp_A \cdot Chp_A + \frac{B_A}{2} \cdot Cs_A + D \cdot C_A + Ci_A = \frac{D}{B_B} \cdot Tp_B \cdot Chp_B + \frac{B_B}{2} \cdot Cs_B + D \cdot C_C; \tag{30}$$

$$\begin{aligned} &\frac{10000}{600} \cdot 2\,h \cdot 30\frac{m.u.}{h} + \frac{600\,parts}{2} \cdot 2\frac{m.u.}{year} + 10\ 000\,parts \cdot 0,15\frac{m.u.}{part} + 6\ 500\,m.u. \\ &\quad = \frac{10\ 000}{400} \cdot 1\,h \cdot 30\frac{m.u.}{h} + \frac{400\,parts}{2} \cdot 2\frac{m.u.}{year} + 10\ 000\,parts \cdot C_C\frac{m.u.}{part}; \end{aligned} \tag{31}$$

$$C_C = \frac{8450}{10000} = 0,845\,\frac{m.u.}{part} \tag{32}$$

In order to interpret the results, it is interesting to represent graphically the unit cost per part versus the number of units manufactured using the three options proposed (*A*: injection moulding, *B*: 3D printing and *C*: 3D printing of optimised product).

To do so, Eqs. (33)–(35) can be used to obtain the figures presented in **Table 3**.

$$C_A = \frac{\left(\frac{X\,parts}{600\,parts} \cdot 2\,h \cdot 30\frac{m.u.}{h} + \frac{600\,parts}{2} \cdot 2\frac{m.u.}{year} + X\,parts \cdot 0,15\frac{m.u.}{part} + 6500\,m.u.\right)}{X\,parts} \tag{33}$$

$$C_B = \frac{\left(\frac{X\,parts}{400\,parts} \cdot 1\,h \cdot 30\frac{m.u.}{h} + \frac{400\,parts}{2} \cdot 2\frac{m.u.}{year} + X\,parts \cdot 2\frac{m.u.}{part} + 0\,m.u.\right)}{X\,parts} \tag{34}$$

X **(parts)**	C_A **(m.u.)**	C_B **(m.u.)**	C_C **(m.u.)**
1000	7.35	2.48	1.32
2000	3.80	2.28	1.12
3671.23	2.18	2.18	1.03
5000	1.67	2.16	1.00
10,000	0.96	2.12	0.96
15,000	0.72	2.10	0.95

The table contains the calculation of the costs for number of parts X = 3671.23 and X = 10,000 in order to see how the costs C_A and C_B as well as C_A and C_C are levelled in the equilibrium points.

Table 3.
Costs of manufacturing per part produced for different demands by processes A, B and C.

$$C_C = \frac{\left(\frac{X\ parts}{400\ parts} \cdot 1\,h \cdot 30\,\frac{m.u.}{h} + \frac{400\ parts}{2} \cdot 2\,\frac{m.u.}{year} + X\ parts \cdot 0,825\,\frac{m.u.}{part} + 0\ €\right)}{X\ parts} \tag{35}$$

As a summary of the entire case study, **Figure 5** shows graphically the three cost models that follow the three alternative processes.

In particular, process A is the more rigid one, requiring specific tooling that has a non-negligible impact in the manufacturing costs of small series of products.

Processes B and C are more flexible, yielding a more constant cost per manufactured unit along the entire study range (from 1000 to 15,000 parts). Process C derives from an optimisation of the product from the original case, and so the cost values remain all times below the ones in process B. Indeed, the evolution of the costs in processes B and C follow an evolution almost parallel throughout **Figure 5**.

The costs of process A experiment a strong decrease along the range represented in **Figure 5**. This causes the cost model of process A to cross the cost models for processes B and C, thus determining two equilibrium points marking the sizes of their associated critical series.

5.2 Application of the DSS to the process of decision-making

The application of DSS to compare and extract information from different processes in order to decide which one would be more favourable has usually a similar structure, based on three stages (e.g., see [35]): (i) identification of product requirements, (ii) proposition of feasible alternative processes and (iii) assessment of the outcomes obtained by each of the proposed processes, if possible, adding best practices information.

Within this scheme, the DSS configuration normally starts with the preparation of a knowledge base with the information of the processes that will be taken into consideration during the assessment. Manufacturing times, cost levels, limitations on the number of parts in a batch and in general all the information like the one contained in **Tables 1** and **2** are usually stored and managed in relational databases. In this way, the knowledge is easy to access, filter, select and represent graphically.

Stages (i) and (ii) are usually undertaken by expert systems (ESs), in which the inference engine launches queries to the knowledge base. The most typical use of

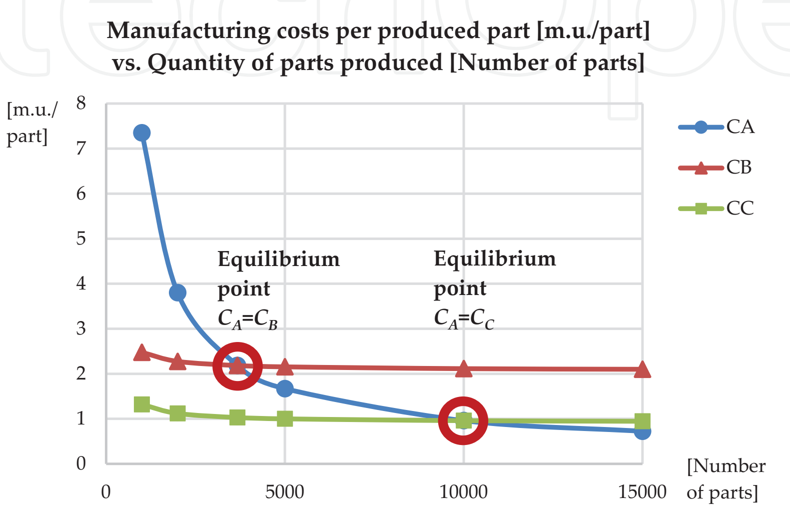

Figure 5.
Costs of manufacturing per part produced as function of the number of manufactured parts by processes A, B and C.

these techniques is by using the '*If-Then-Else*' queries supported on a rule-base knowledge (rule-based diagnosis). Sometimes, if the process complexity is high, it could be useful to implement the knowledge on cases (case-based diagnosis) or even models (model-based diagnosis). This screening technique is useful for the DSS during the first steps to understand the nature of the products that require to be manufactured and so to define the processes that should be shortlisted for in-detail analysis. In the case study discussed in the present chapter, the expert system could have prescribed either injection moulding (process *A*) or additive manufacturing (process *B*) as feasible alternatives.

Once the shortlist of two or three processes has been configured, it is time to provide qualitative and quantitative outputs (iii). In effect, the expert system can provide information on which features of the part can be manufactured straight-forward and which cannot. In extreme impracticable cases, the ES would discard the processes that would not be feasible. However, for the processes shortlisted, some small tuning could be necessary or advisable to be performed before producing the part. At this stage, there is a general need to increase the system response in quantitative and qualitative aspects.

Concerning the quantitative aspects, further results can be achieved using artificial neural networks (ANNs). ANNs can be used, for example, to simulate the manufacturing process of the same part with the same technology in two different units of equipment-for example, two machines in different production sites-that yield different process variables-for example, because one is bigger than the other, or because they are placed in different regions with different cost schemes. Also, the ANNs could be used to assess the consequences of undertaking product modifications like the optimisation simulated in the case study to achieve the part as process *C* [16].

In addition, many times the qualitative analysis can be further deployed with fuzzy logic (FL) techniques. In this sense, the application of fuzzy ontologies can be helpful to translate linguistic terms and qualitative values into numerical properties and specific states. For example, it is common to receive the customer need of a product to have '*good mechanical behaviour*' and/or '*low permeability of liquid through its walls*'. In these cases, fuzzy can help in quantifying this information. The quantification could be good to help configure a balanced scorecard for decision-taking [17].

Finally, the user interface in the DSS should present the user the conclusions of the analysis. It is preferable to have it in a mix of quantitative and qualitative description. The numerical report is recommended to be as the one presented in **Table 3** and **Figure 5**, where the economical cost schemes and levels are clear. Also, other related information such as a scenario analysis for different batch sizes or the study of the different manufacturing delivery times would be highly acknowledged by the users. The qualitative report should include information on the best practices and some part improvement counselling. It would be highly recommendable to be presented in the form of a colour scale-for example, for which each assessed variable ranked from 0 to 5-and if possibly displayed in a visual mode (in a dot plot or a spider diagram form).

This '*vectors*' of information could finally be compared by the user, probably assisted by the numerical optimisation of some objective function in order to finish with a multi-criteria decision support information, capable of being run by non-expert users.

A further refinement of the DSS could deploy the use of AI techniques to increase autonomously the information contained in the knowledge base. The current systems installed frequently utilise on-line information as a procedure for data mining for the processes taken into consideration, while the most common practice is to incorporate it from human experts through specific expert user gates in the system. However, there is still a big opportunity to deploy systems that could incorporate information on the obtained results directly from the manufacturing facilities, or even better from the customer use point, once the part is performing the task for which it was originally acquired.

6. Conclusions

In the current paradigm of Industry 4.0, it is more than ever more necessary to be able to take the best decisions when it comes to manufacturing. Indeed, the industrial means available nowadays postulate that many different possibilities of processes and strategies can be viable in order to produce a specific part.

In this context, Section 2 of the present chapter has formalised a general model for evaluating costs in manufacturing process, which also considers the contribution to the costs of stocking the parts in the manufacturing premises.

Following that, Section 3 has formalised the necessary rules to determine the critical batch *Bc* between two different possible manufacturing processes for a part, serving as a decision-taking criterion for selecting the most productive scenario. In addition, Section 3 has also addressed the evaluation of the size of a critical series *Sc* for taking decisions based on the manufacturing long run. Complementary to the critical batch launch, Section 3 has also discussed the so-called *degree of postponement*, in order to give additional insight into how to raise the efficiency and effectiveness of the production processes.

Section 4 has drawn a concise review of the literature on decision support systems (DSS) used to tackle production strategies decision-taking. At this point, it is clear that the groups of factors affecting the decisions can be categorised into (i) technology capabilities, (ii) production organisation constraints and (iii) market-demand orientation.

Finally, Section 5 has illustrated the decision-taking processes and results with a simple yet realistic industrial case study in which it is possible to utilise two different existing in-house processes *A* or *B* for obtaining the same part *P*. In the case study, the cost models of both processes have been analysed and the determination of the critical batches, critical series as well as the total costs per process has been targeted. In addition, it has been numerically determined and the possibility to undertake some process optimisation to reduce the cost level of one of the technologies envisaged has been studied. Based on this case study, the possible application of a DSS to the decision-making framework has also been outlined and the different AI techniques that could be developed at each stage have been described.

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Conflict of interest

The authors declare that they have no conflict of interest on this publication.

Author details

Joaquim Minguella-Canela[1,2]* and Irene Buj Corral[1]

1 Mechanical Engineering Department, Universitat Politècnica de Catalunya – BarcelonaTECH (UPC), Barcelona, Spain

2 Fundació Privada Centre CIM, (CIM UPC), Barcelona, Spain

*Address all correspondence to: joaquim.minguella@upc.edu

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Chapter

Developing Cognitive Advisor Agents for Operators in Industry 4.0

Alejandro Chacón, Cecilio Angulo and Pere Ponsa

Abstract

Human cyber-physical systems (CPS) are an important component in the development of Industry 4.0. The paradigm shift of doing to thinking has allowed the emergence of cognition as a new perspective for intelligent systems. Currently, different platforms offer several cognitive solutions. Within this space, user assistance systems become increasingly necessary not as a tool but as a function that amplifies the capabilities of the operator in the work environment. There exist different perspectives of cognition. In this study cognition is introduced from the point of view of joint cognitive systems (JCSs); the synergistic combination of different technologies such as artificial intelligence (AI), the Internet of Things (IoT) and multi-agent systems (MAS) allows the operator and the process to provide the necessary conditions to do their work effectively and efficiently.

Keywords: cognition, multi-agent system, advisor, operator

1. Introduction

The continuous introduction of technology in the industrial environment is a main generator of changes in architectures, models and work styles in the industry. Currently, Industry 4.0 signifies a great opportunity for operators to become a part of the new manufacturing systems [1]. On the one hand, operators generate information and data to programme machines and robots and optimise process flows; on the other hand, they receive useful support for their work as well as effective cooperation with intelligent systems [2]. This bidirectional dialogue allows new types of powerful interactions between operators and machines. Hence, a new kind of workforce should be trained in order to obtain a significant impact on the development of the industry [3].

The use of artificial intelligence (AI) techniques to enhance the lifelong learning experience of humans has evolved in literature from the early works on *intelligent tutor systems*, where AI is used as a tool to monitor and facilitate the user learning process, to the creation of *human-computer collaborative learning* systems (HCCL) [4], where AI entities become members of a group of mixed human and artificial learners. Through HCCL systems, humans acquire problem-solving or decision-making capabilities in a particular domain in simulated or real situations.

In the Industry 4.0 scenario, AI entities can be endowed as cognitive advisor agents implemented in the form of either voice assistants or embodied agents, in

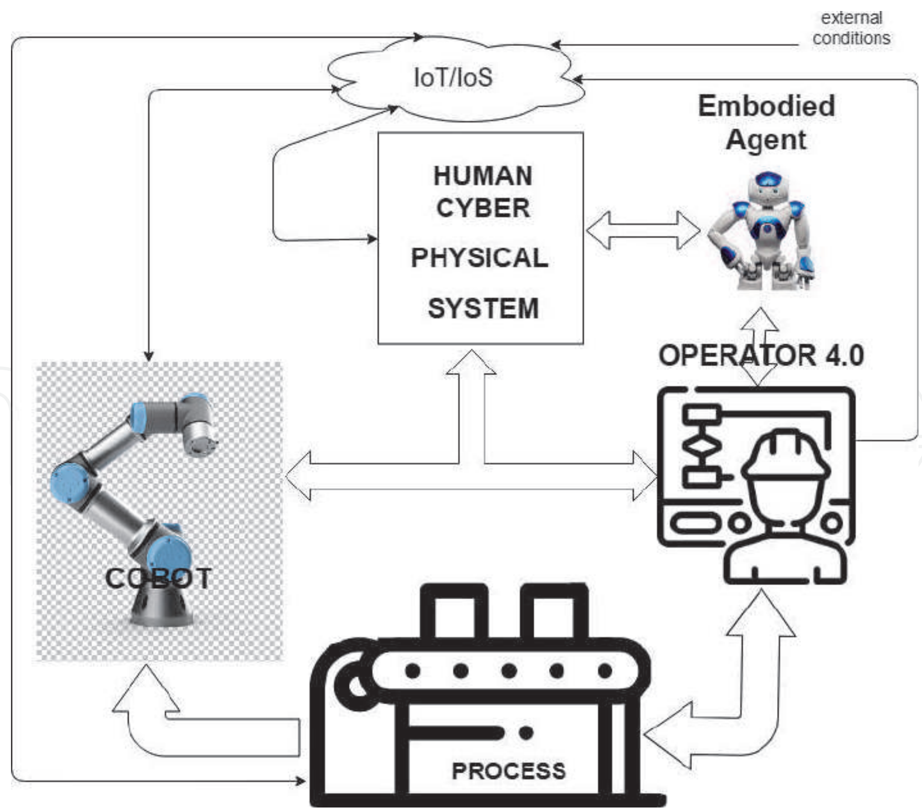

Figure 1.
Proof of concept. The operator 4.0 is assisted by the embodied agent to collaborate with the cobot in the process.

order to propose collaborative working behaviours between machines and humans. The implementation of these systems in manufacturing pushes towards factories characterised by the symbiosis of human automation [5], where machines cooperate with humans, both parts having the opportunity to lead the cooperative task at hands.

The challenge motivating this research is to define a human-centred architecture to design, implement and evaluate cognitive advisor agents in the framework of a human cyber-physical production system (H-CPPS) [2, 6] which supports the operator in Industry 4.0 to accomplish their job into an automation system [7] in a more efficient and effective form. The proposed overall H-CPPS architecture will be evaluated through a proof of concept based on a multi-agent system (MAS) implementing a cognitive robot (embodied agent) to assist the operator (operator 4.0) in a collaborative work with a cobot. A scheme of the operator—cobot—assistant robot symbiotic system is shown in **Figure 1**.

This chapter is structured as follows. Firstly, the current Industry 4.0 paradigm is introduced, and the role of human operator in this domain is shown. Next, the proposed human cyber-physical production system architecture is introduced. Moreover, the approach of this architecture to cognitive tasks is presented. The cognitive advisor vision to be endowed into the previous architecture is finally introduced. Conclusions and future research lines are closing the chapter.

2. The operator's workspace in Industry 4.0

The *operator 4.0* concept is defined in [2, 8] in a general form as an operator in an industrial setting assisted by technological tools. Although the increase in the degree of automation in factories reduces costs and improves productivity, in the Industry 4.0 vision, differently of computer-integrated manufacturing (CIM), human operators are yet key elements in the manufacturing systems. In fact, the increasing degree of automation 'per se' does not necessarily lead to enhanced operator performance.

The continuous innovations in the technological areas of cyber-physical systems (CPS), the Internet of Things (IoT), the Internet of Services (IoS), robotics, big data, cloud and cognitive computing and augmented reality (AR) result in a significant change in production systems [9, 10]. Empowered with these new skills, cyber-physical systems can take part, for instance, in tasks of planning and disposition, eventually to manage them. Machines take care of the adequate supply of material, change the production method to the optimal one for the real product or devise a new plan themselves [11]. This technological evolution generates, among others, the following impacts on the operator:

- The qualification of manual tasks decreases.
- The operator can access all the necessary information in real-time to take decisions.
- Intelligent assistance systems allow decisions to be taken more quickly and in a short space of time.
- Co-working in the workspace between machines and people requires less effort and attention.
- Human implementation and monitoring are more relevant than ever.

The emerging technologies in Industry 4.0 [12] as well as current development of AI technologies are allowing that cyber-physical systems oriented to human-machine interaction be moving from only a physical interaction vision paradigm to also a cognitive one (see **Table 1**). The operator should be able to take the control and supervise the automated production system. However, the increasing information and communication power of these systems leads to a complexity that is not understandable by the current standard user interfaces employed in the industry. Consequently, the operator would need support to keep the system under stable requirements. Moreover, the operator could get the system work plan (factory, not shift supervisor), and therefore the operator would need additional information during field operation, which requires access to location-independent information as well as a situation-oriented and task-oriented information offer [13].

As a result of this paradigm shift, new forms of interaction appear in the field of human-machine interface (HMI), in the form of intelligent user interfaces, such as operator support systems (OSS), assistance systems, decision support systems and intelligent personal assistants (IPAs) [7]. In the context of smart, people-centred service systems, cognitive systems can potentially progress from tools to assistants to collaborators to coaches and be perceived differently depending on the role they play in a service system.

	Physical	**Cognitive**
Routine	Traditional automation	Automated learning techniques
Nonroutine	Collaborative robots	Intelligent assistants (IA)

Table 1.
Vision of physical and cognitive automation.

Assistance systems support the operator as follows [14]:

- From a human-centred design approach, it expressly considers the identification of user context, the specification of user requirements, the creation of design solutions, and the evaluation of design solutions. Moreover, it provides an appropriate amount of information in a clear way.

- As a decision-maker in production control, with information acquisition, data aggregation/analysis of information and operation choice.

However, it should be clarified that the final decision always remains in the human operator side, thus maintaining the principle of human centrality.

Regarding the tasks and the role of the operator, an increase in the proportion of *complex cognitive tasks* is expected, hence increasing the needs for coordination or organisation of production resources, as well as the control and monitoring of complex production systems.

The literature shows that a significant change in this relationship from purely physical to cognitive refers to the human-machine interface, which encompasses the interaction between operators and a set of new forms of collaborative work. The interaction between humans and CPS is produced by either direct manipulation or with the help of a mediating user interface. Such a close interaction between humans and CPS also raises socio-technological issues regarding autonomy and decision-making power. Cybernetics provides an answer on how a system that controls another system can compensate for more errors in the control process by having more operational variety. As the most flexible entity in the cyber-physical structure, the human will assume the role of a higher-level control instance [10]. Through technological support, it is guaranteed that operators can develop their full potential and adopt the role of strategic decision-makers and flexible problem solvers, thus managing the increasing technical complexity.

3. Human cyber-physical production systems

Cyber-physical systems are one of the fundamental pillars of Industry 4.0 [10, 15, 16]. According to the National Institute of Standards and Technology (NIST), cyber-physical systems are intelligent systems, including interactive networks, designed of physical and computational components. These systems integrate computing, communication, detection and performance with physical systems to fulfil time-sensitive functions with varying degrees of interaction with the environment, including human interaction (see **Figure 2**). These systems are conceived as components in the production system able of executing physical processes in cooperation with other entities. Systems can adapt independently to changing circumstances, by learning from the additional information coming from the sensors [6].

Usually, each component of the CPS takes the necessary control decisions related to the physical aspects of the underlying production system and communicates control decisions, system states and behaviour patterns. Currently, the possibility to combine existing technologies such as multi-agent systems, service-oriented architectures (SOA), the Internet of things, cloud communication, augmented reality, big data or machine-to-machine communication (M2M) [9] has empowered the features and functions of these systems so that levels of cognition in the cooperation, beyond physical interaction, can be also considered.

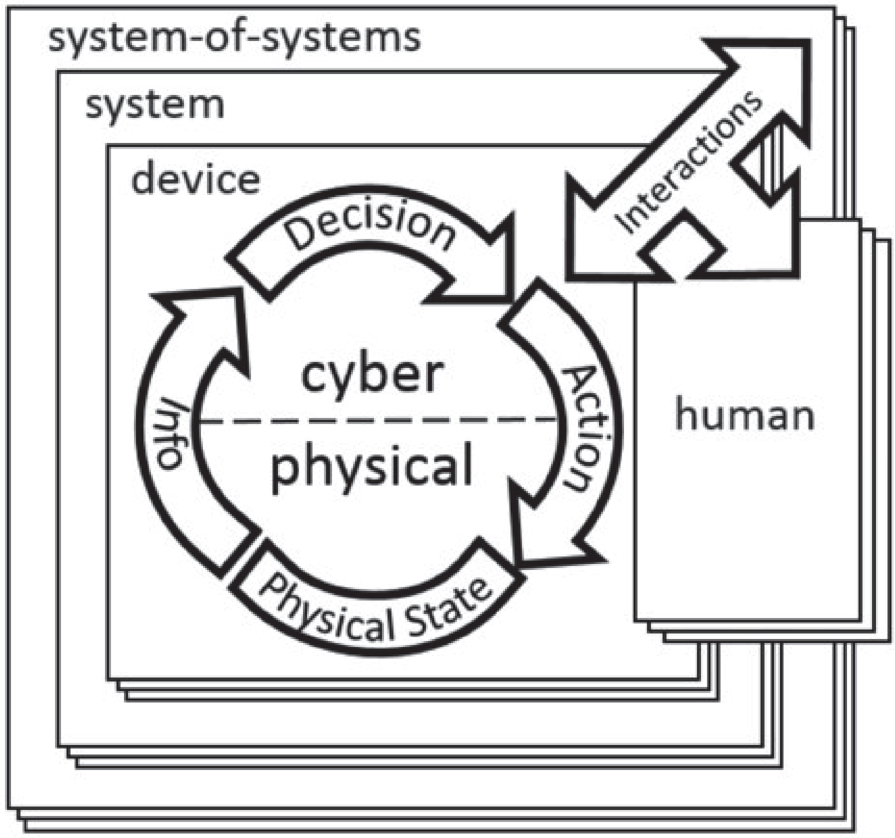

Figure 2.
CPS conceptual model [17].

In the approach with humans in the interaction, new models of CPS have emerged which focused on improving the capabilities of operators, such as cyber-physical human system (CPHS) [17] and human cyber-physical production system [2]. CPHS is defined as "a class of sociotechnical systems critical for security in which the interactions between the physical system and the cybernetic elements that control its operation are influenced by human agents." Our research, however, focuses on H-CPPS, defined as "a work system that improves the capabilities of operators thanks to a dynamic interaction between humans and machines in the cyber and physical worlds through intelligent human-machine interfaces." The objectives for H-CPPS are achieved through the interactions between the physical system (or process) to be controlled, cybernetic elements (i.e. communication links and software modules) and human agents that monitor and influence the functioning of the cyber-physical elements.

In both definitions we can highlight the role of the operator within the control loop. In human-oriented architectures, there is the ability to feedback the information (see **Figure 3**) at each level, because inherent intelligence of human operators can be used naturally for self-adaptation, corrective and preventive actions. For the H-CPPS approach, its levels' configuration acts as a supervisory control to ensure that decisions made at the cognitive level are implemented and that corrective or adaptive actions are carried out by the human worker [18].

H-CPPS are very dynamic and complex systems being subject to a certain degree of unpredictable behaviour of both the environment and the user. These conditions generate several challenges related to the administration of H-CPPS that require run-time capabilities allowing the system to detect, monitor, understand, plan and act on those not predicted changes while minimising (and potentially eliminating) system downtime. In order to develop our cognitive advisor agent for operators, we start by defining three dimensions of H-CPPS: *cybernetic*, *physical* and *human*. Each

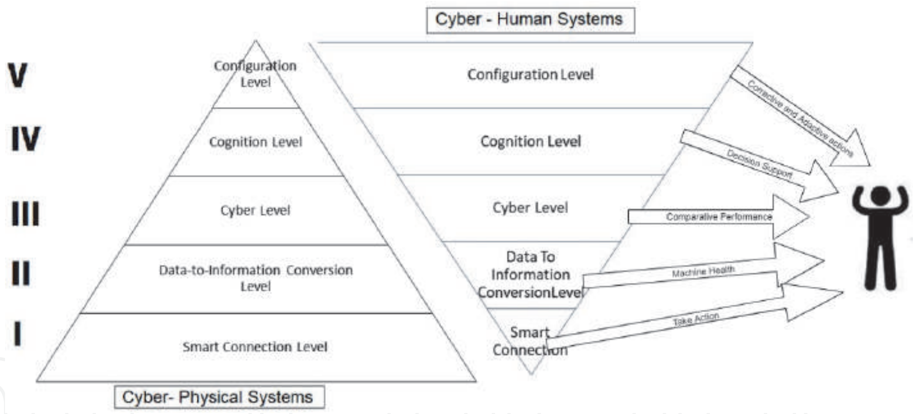

Figure 3.
CPS vs. H-CPPS model.

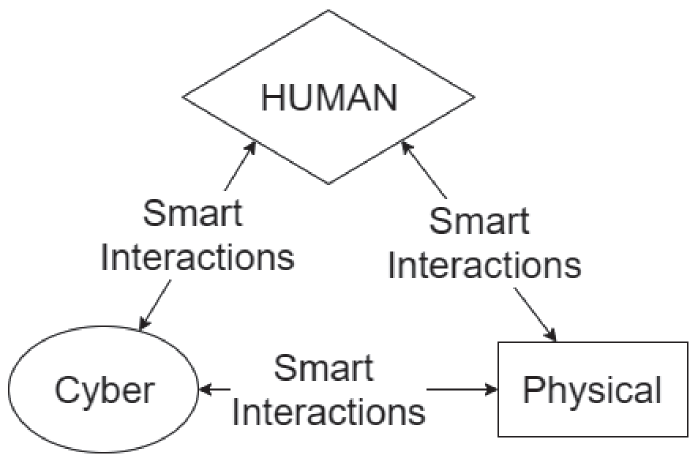

Figure 4.
Three dimensions of H-CPPS.

dimension is connected to the other ones through intelligent interactions (see **Figure 4**).

The physical dimension includes all the resources connected to the production system through sensors and actuators. The cybernetic dimension describes all computing, network and cloud infrastructures that communicate data, processes and software resources. Finally, the human dimension describes human elements, as well as their situations based on their objectives and context. The human dimension is especially relevant for this research, focused in aligning the objectives of H-CPPS with the achievement of the personal goals of the users.

3.1 Agent-based approach to H-CPPS

The applications of artificial intelligence techniques related to humans in the work environment are guided by four possible paths in human cyber-physical systems (see **Table 2**). As the 'human in the loop' is considered in H-CPPS, intelligent assistance systems are the approach to be developed in our research.

Nowadays, different architecture patterns and implementation technologies have been developed and applied to process and exchange information allowing H-CPPS components to make their decisions. They range from service-oriented architectures that exploit technologies such as web services to agent-based architectures that exploit solutions compatible with Foundation for Intelligent Physical Agents (FIPA) [19]. However, they also come with their own set of challenges.

	Human in the loop	No human in the loop
Hardwired specific systems	*Assisted intelligence*: AI system that assist human in making decisions or taking actions, hardwired systems that do not learn from their interactions	*Automation*: Automation of manual and cognitive tasks that are either routine or nonroutine. This does not involve new ways of doing things—automates existing task
Adaptative systems	*Assisted intelligence*: AI systems that augment human decision-making and continuously learn from their interactions with humans and the environment	*Autonomous intelligence*: AI systems that can adapt to different situations and can act autonomously without assistance

Table 2.
Path AI in human cyber-physical systems.

Multi-agent systems [20] are an example of architecture applicable to the implementation of H-CPPS. More specifically, industrial agents [21, 22] address industry requirements in productive systems. MAS expose system characteristics such as autonomy, cooperation, intelligence, reactivity and proactivity, which allows intelligence to be distributed among a network of control nodes and, consequently, adapts effectively to distributed control systems, that is, by implementing H-CPPS solutions [21]. While the use of MAS for control process can be considered as a mature architecture pattern, its application in the industry is still limited [23].

In order to define our agent-based approach to H-CPPS systems, two types of interactions should be identified (see **Figure 4**):

- Interaction between agents (only considering the cyber dimension)
- Interaction between agents (cyber dimension) and hardware automation control devices (physical dimension)

For the first type of interaction, FIPA has established guidelines to regulate the development of agent-based systems. It is a collection of standards that are grouped into different categories, that is, applications, summary architecture, agent communication, agent management and message transport agent. For the second type of interaction, related to the interconnection of the agent and the physical automation control device [24], standardised practices are not yet defined, allowing to simplify and make transparent the process of integration of physical and cybernetic counterparts.

Finally, it should be noticed that agents, as an enabling technology to manage smart approaches, endow inherent characteristics (including autonomy, negotiation, mobility) which could be more beneficial when combined with *distributed intelligence* approaches and lead to better services and applications at the edge [16].

3.2 Human roles in H-CPPS

For the moment, the cyber and the physical dimension have been considered in our agent-based approach. However, while in a human-centred architecture, the roles of humans in cyber-physical human systems (H-CPPS) must be also defined.

In the models of human-automation interaction, attention is paid to whether human assumes control of the system [25]. In H-CPPS systems, however, human intervention is focused in more aspects: the dialogue with other agents, decision-making and information supply. In this sense, one research line is about the definition of a human model as a part of the full H-CPPS model. However, human models defined as a transfer function leads to a poor approach. Some researchers expand this approach by developing analytic human models that reflect *cognitive abilities* in the interaction with cyber-physical systems [17]. On the other hand, a H-CPPS requires flexibility. An adaptive H-CPPS responds to unexpected or novel situations (replanning, setting new goals, learn from experience), and the definition of the role of human (passive or active performer) is required [17]. Human roles examples in H-CPPS are, for instance:

- Supervisor (human on the loop): Approve CPS decisions; reallocate tasks between human and CPS.

- Controller (human in the loop, operator 4.0): Interact with sensors and actuators; use of augmented reality technology; collaborative task with a cobot.

Merging human roles with CPS roles in order to define the functional architecture of a H-CPPS leads our research to the definition of a *joint cognitive system* (JCS), its basic aim being to achieve a high level of successful performance managing the human cognitive load in the process.

4. Joint cognitive system

The current development of technology allows us to reach the level of cognition in H-CPPS (see **Figure 3**) [18]. However, the understanding of cognition generates debates because it can be approached from several domains, mainly from psychology through mental models, and from cognitive systems engineering (CSE) to applications in practice.

A joint cognitive system acknowledges that cognition emerges as goal-oriented interactions of people and artefacts in order to produce work in a specific context and at the level of the work being conducted. It does not produce models of cognition but models of **coagency** that corresponds to the required variety of performance and thereby emphasises the functional aspects [26].

In this situation, complexity emerges because neither goals nor resources nor constraints remain constant, creating dynamic couplings between artefacts, operators and organisations. The CSE approach focuses on analysing how people manage complexity, understanding how artefacts are used and understanding how people and artefacts work together to create and organise joint cognitive systems which constitutes a basic unit of analysis in CSE. Human and machine need to be considered together, rather than separate entities linked by human-machine interactions [27].

In the domain of CSE, focus is on the mission that the joint cognitive system shall perform, avoiding vagaries into its human resemblances. It performs cognitive work via cognitive functions such as communicating, deciding, planning, and problem-solving (**Figure 5**). These sorts of cognitive functions are supported by cognitive processes such as perceiving, analysing, exchanging information and manipulating.

The importance of cognition, regardless of how it is defined, as a necessary part of the work has grown after the industrial revolution:

- Cognition is distributed rather than isolated in the human operator's mind.

- Operator does not passively accept technological artefacts or the original conditions of their work.

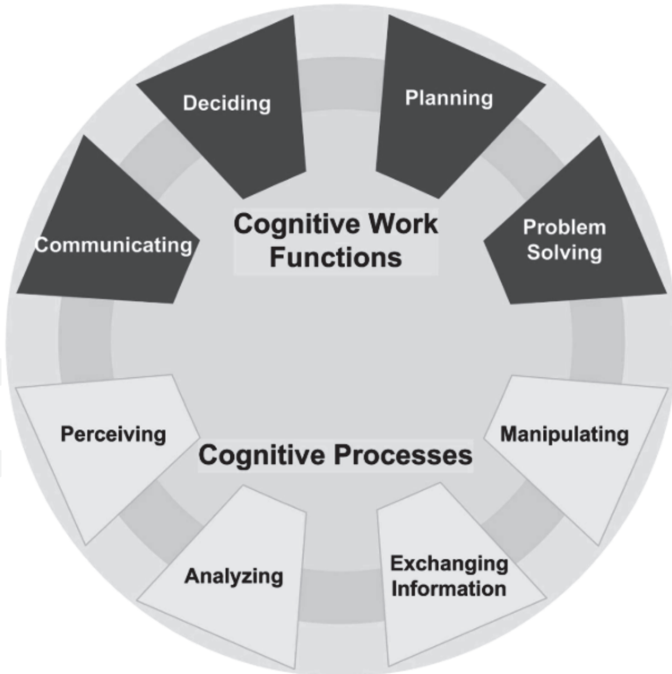

Figure 5.
Cognitive work functions and cognitive processes.

- Technological development is rampant; this entails the development of work with inevitably greater *operational complexity*.
- Technology is often used in ways that are not well adapted to the needs of the operator.

There is no turning back, the evolution of information technology, digital transformation and the Fourth Industrial Revolution requires that processes be more cognitive, automatic and efficient.

4.1 The cognitive design problem: the FRAM tool

As the automation of complex processes becomes more achievable, the need for engineering procedures that help decide what and how to automate becomes more important to the safety, flexibility and performance of automation use. The implementation must satisfy general criteria such as *minimising workload*, *maximising awareness of what is going on* and *reducing the number of errors*. The basic problem therefore is to reduce the cognitive demands of the tasks being performed by the operators involved in the system while maintaining fully their ability to function within their given roles [28].

JCSs are characterised by three principles [27]: (a) goal orientation, (b) control to minimise entropy (i.e. disorder in the system) and (c) coagency at the service of objectives.

In order to understand the sociotechnical system, the functional resonance analysis method (FRAM) [29] can be used, which allows to have a model generated by the application itself. The FRAM can be described as a method that is used to produce a model, instead of a method that is derived from a model. It proposes that everyday events and activities can be described in terms of *functions* involved without predefined specific relations, levels or structures. Instead, the FRAM assumes that the behaviour of functions, hence the outcomes of an activity or process, can be understood in terms of *four basic principles* described in the following statements. Moreover, the not predefined functions are described using *six aspects*.

The principles of FRAM are:

1. The equivalence of successes and failures: acceptable outcomes as well as unacceptable outcomes are due to the ability of organisations, groups and individuals successfully to adjust to expected and unexpected situations.

2. Approximate adjustments: things predominantly go well, but also they occasionally go wrong.

3. Emergent outcomes: the variability of two or more functions can be combined in unexpected ways that can lead to results that are unpredictable and disproportionate in magnitude, both negative and positive.

4. Functional resonance: the variability of one function may in this way come to affect the variability of other functions in analogy with the phenomenon of resonance.

In FRAM a function represents acts or activities—simple or composite—needed to produce a certain result. Examples of simple human functions are to triage a patient or to fill a glass with water. The organisational function of the emergency room in a hospital, for example, is to treat incoming patients, while the function of a restaurant is to serve food. Finally, composite functions include, for instance, a flight management system.

In the description of functions, an important distinction can be made between tasks and activities, corresponding to the distinction between work-as-imagined (WAI) and work-as-done (WAD). A task describes work as designed or as imagined by managers. An activity describes work as it is actually performed or done. FRAM primarily focuses on activities as they are done or WAD but can of course also be used to model WAI.

To basically illustrate the use of FRAM, a pick and place system with a robot is shown in **Figure 6**. The system is based on filling boxes with cylinders. The cylinder supplier is in position *Warehouse* and the destination box in position *Box*. The FRAM model should describe functions and their potential couplings for a typical

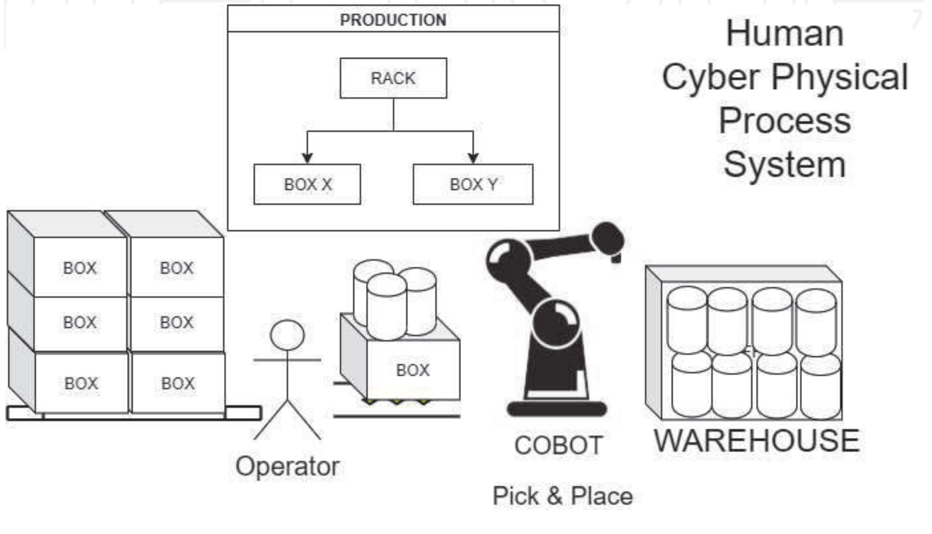

Figure 6.
Example of a H-CPPS.

situation but not for a specific one. Hence, it is not possible to certainly determine whether a function always will be performed before or after another function. It can only be determined when the model is instantiated. At the start, functions are identified in a first-independent version about execution (see **Figure 7**).

The development of the model can continue in several ways—none of them being preferable over the others. One way is to look at the other functions in the same way and try to define as many of their aspects as seems reasonable and possible. Another way is try to define aspects that are incompletely described in the current version of the model. The basis of the FRAM is the description of the functions that make up an activity or a process. The functions of different tasks have been assigned depending on who does it, (human, cobot, process) in the H-CPPS (see **Figure 8**). The relationships are not specified nor described directly, and the FRAM Model Visualiser (FMV) in fact does not allow lines or connectors to be drawn between functions. The relationships are instead specified indirectly via the descriptions of the aspects of functions. The common technical term for such relations is *couplings*.

Couplings described in a FRAM model through dependencies are called *potential couplings*. This is because a FRAM model describes the potential or possible relationships or dependencies between functions without referring to any particular situation. In an instantiating of a FRAM model, only a subset of the potential couplings can be realised; these represent the *actual couplings* or dependencies that have occurred or are expected to occur in a particular situation or a particular scenario [29].

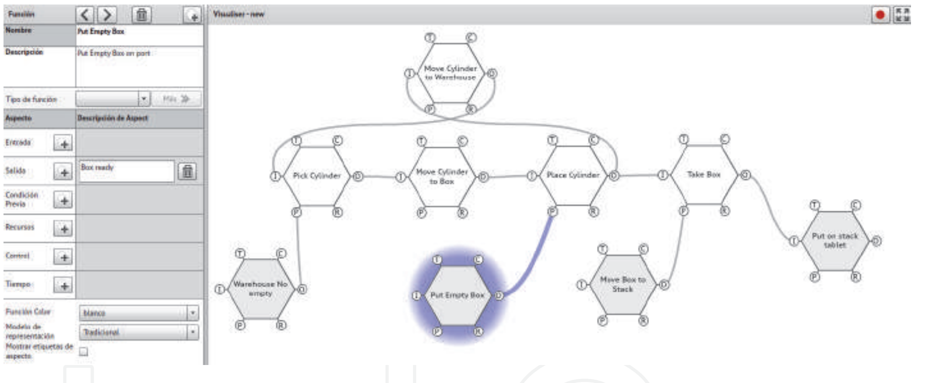

Figure 7.
The FRAM model for a pick and place function ver1.0.

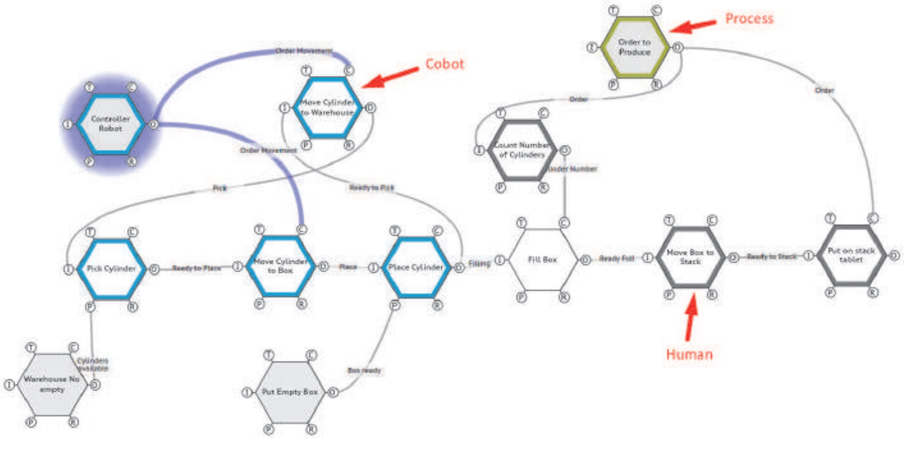

Figure 8.
The FRAM model for a pick and place function/assignation functions.

Hence, basically we can highlight the following useful features for our study:

- Purpose: A FRAM analysis aims to identify how the system works (or should work) for everything to succeed (i.e. everyday performance) and to understand how the variability of functions alone or in combination may affect overall performance.

- Model: A FRAM model describes a system's functions and the potential couplings among them. The model does not describe or depict an actual sequence of events, such as an accident or a future scenario.

- Instantiation: A concrete scenario is the result of an instantiation of the model. The instantiation is a 'map' about functions coupling or how they may become coupled, under given—favourable or unfavourable—conditions.

The use of FRAM as a tool for the analysis of cognitive tasks would allow us to understand about JCS works, identify its critical points and the propagation of the relationships between functions and understand the distributed cognition and coagency between the human and the machine.

5. Cognitive advisor agents

Cognitive systems are capable of humanlike actions such as perception, learning, planning, reasoning, self- and context-awareness, interaction and performing actions in unstructured environments. The functionality of the cognitive system includes enabling perception and awareness, understanding and interpreting situations, reasoning, decision-making and autonomous acting.

Due to their cognitive capabilities, humans are superior to fully automated mass production systems in adapting to flexible, customised manufacturing processes. Yet, the increasing specialisation is creating more and more complex production processes that require elaborate assistance in task execution. Furthermore, machines are much better at performing repetitive, heavy-load tasks with high precision and reliability.

The cognitive system provides the best possible assistance with the least necessary disruption. In this context, a cognitive system enables the realisation of an adaptive, sensitive assistance system that provides guidance only if needed and based on operator skill (e.g. a 1-day 1 trainee versus a worker who has been with the company for 30 years), cognitive load and perception capability—in other words, it provides the best possible assistance with the least necessary disruption. The adaptivity of the feedback design enables the education of novices in on-the-job training scenarios, integrating novices directly into the production process during their 1-month training period without the need for specialists [30].

At present, H-CPPS can be endowed with powerful intelligence by leveraging next-generation AI, which allows three main technological features: the first, most critical, characteristic is that the cyber systems have the ability to solve uncertain and complex problems; furthermore, problem-solving methods shift from the traditional model of emphasising causality to an innovative model of emphasising correlation and further towards an advanced model of deeply integrating correlation with causality. This shift will lead to fundamental improvements in the modelling and optimization of manufacturing systems.

The second most important feature is that cyber systems have capabilities such as learning, cognitive skills and the generation and better use of knowledge; this will

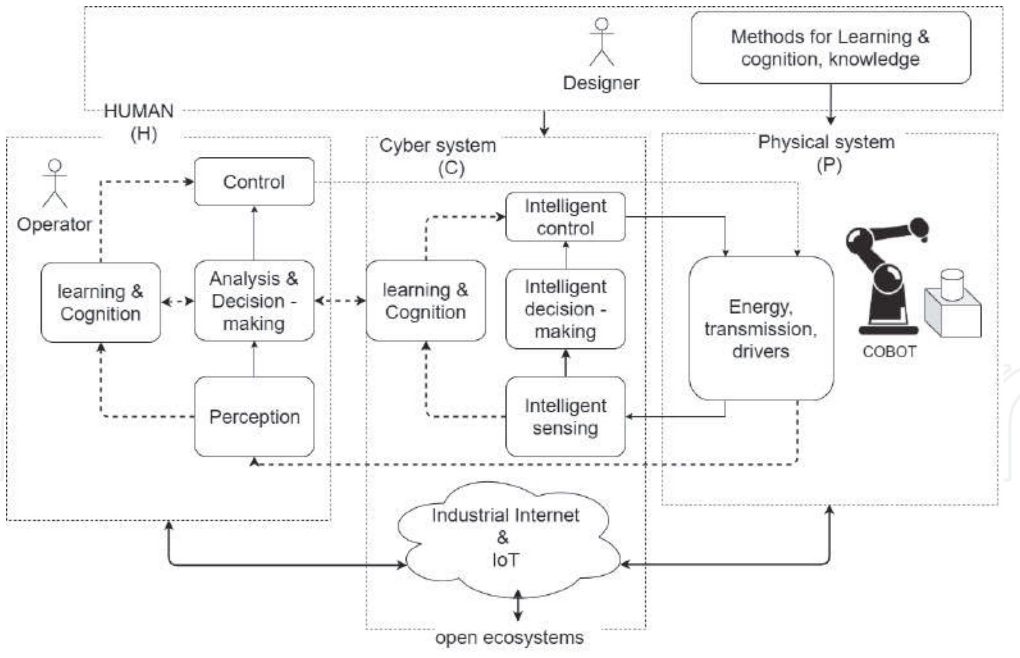

Figure 9.
H-CPPS for Industry 4.0.

lead to revolutionary changes in the efficiency of the generation, use, importation and accumulation of knowledge and to the significant promotion of the marginal productivity of knowledge as a central productive element.

The third feature is the formation of augmented human-machine hybrid intelligence, which provides full scope and synergistically integrates the advantages of human intelligence and artificial intelligence. This will result in the innovation potential of humans being completely released, and the innovation capabilities of the manufacturing industry greatly increase. With these technological advances and the advances in the Internet of Things and cloud computing, cognitive solutions are available that will allow the operator to develop their work in an efficient, effective and, above all, empowered position. **Figure 9** introduces an architecture with cognition for the Industry 4.0. Two characteristics are important to highlight, the first the Internet of Things and its solutions in the cloud which allow to reach levels of cognition for all operator functions and the second the cognitive capacity of H-CPPS systems.

6. Conclusions

The development of emerging technologies around Industry 4.0 is changing the paradigm of the intelligent industry to the cognitive industry, where it seeks to harness the cognitive capabilities of the systems to meet the new demands of the industry. Challenges presented by technological development that focused on industry require the integration of different areas of science, engineering and technology. Today, synergy combinations are required to support the development of intelligent and cognitive solutions. Understanding of sociotechnical systems from the perspective of joint cognitive systems shows in the first place the current ability to provide the operator with functions and tools that allow him to amplify his abilities, in particular the cognitive ones for which it can be seen that there are different cognitive tools, thanks to which cognitive solutions are capable of being applied.

Author details

Alejandro Chacón[1,2†], Cecilio Angulo[2*†] and Pere Ponsa[2]

1 Universitat de las Fuerzas Armadas 'ESPE', Quito, Ecuador

2 Universitat Politècnica de Catalunya (UPC), BarcelonaTech, Barcelona, Spain

*Address all correspondence to: cecilio.angulo@upc.edu

† These authors contributed equally.

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Chapter

Current Transducer for IoT Applications

Erik Leandro Bonaldi, Levy Ely de Lacerda de Oliveira, Germano Lambert-Torres, Luiz Eduardo Borges da Silva and Vitor Almeida Bernardes

Abstract

The evolution of communication technology and the reduction of its costs have driven several advances in measurement systems. Points that could not be measured before can now be monitored. Points with difficulty to reach or with major security restrictions can begin to have their quantities measured and informed to control centers. This chapter presents one of these evolutions showing a current transducer (CT), which can measure this magnitude, make an initial treatment of the signal, and transmit it to a panel or control center. Besides, this current transducer does not require an energy source to operate, being self-powered by the current it is measuring. Because it is inexpensive, it can be spread through the facilities, supplying the current at various points of the observed electrical network. With signal treatment, useful information can be inserted in this device so that it informs already preprocessed elements to reading devices, becoming part of the world of IoT. This article presents its use in motor condition monitoring at the Pimental hydroelectric power plant.

Keywords: measurement, current transducer, IoT, IIoT, energy monitoring, condition-based maintenance

1. Introduction

In recent times, new scenarios, many of them futuristic and revolutionary, have emerged based on technological advances in two areas, the development of processors with high processing power and high energy efficiency [1] and the development of communication protocols with high transfer rates and low consumption [2].

On the one hand, these advances have stimulated a revolution in the world of sensors that has been called the "Industrial Internet of Things" (IIOT) [3–5], where it is seen that all devices will present, shortly, some kind of intelligence and interconnection through the Internet. On the other hand, in the industrial environment, another revolution related to these technological advances has been establishing, the so-called fourth Industrial Revolution, or Industry 4.0 [6, 7], where the physical systems of the factory floor will have their parameters monitored and digital models of your operative and maintenance condition will be updated for decision-making and optimization purposes.

And more, another equally strong trend, due to concerns about the environmental impact generated by all this diffusion of consumer electronics and industrial electronics, is the energy collection from the environment, named "energy harvesting." This tendency is based on the energy collection from the environment to drive highly efficient electronics, avoiding the dependence of the electrical system and eliminating the use of batteries or significantly reducing it. Another advantageous aspect of devices with power collection is related to the ease of installation, since power sources and cables connected to power outlets are not required, configuring a wireless power supply.

In accordance with those recent trends, this chapter proposes a wireless self-supplied current transducer (CT) as an IIOT application for induction motor monitoring. Section 2 presents an overview of the proposed current transducer and the modeling considerations about the measurement and power extraction CTs. In Section 3, the basic components used in the implementation of the proposed current transducer are presented. Section 4 considers the available wireless interface standards and details the chosen one. The final assembly of the resulting prototype is presented in Section 5. In Section 6, test results are presented attesting the prototype performance. And Section 7 presents the conclusions.

2. Overview of the current transducer

Figure 1 presents the general overview of the developed current transducer, where there are two current transducers, one for measurement and the other for energy extraction. The system is complete with a wireless communication module, IEEE 802.11 Standard (Wi-Fi) [8]. The device presented in this chapter can be applied widely throughout the industrial sector, regardless of its specificity, since the need of current measurement for energy monitoring or monitoring of the condition of machinery is widespread enough.

2.1 Measuring CT modeling

For monitoring large-scale equipment, the measurement units can be considered ideal transformers in the frequency range of interest between ~ 5 and ~ 3 kHz. The only concern is the input impedance of the AD converter which is in parallel with the "shunt" resistor in a direct connection or the input impedance of the amplifier making the buffer function to protect the AD converter in an indirect connection. However, in both cases, the input impedance tends to be much higher than 50 Ω. For a direct connection to the AD converter, the input impedance for the high-resolution mode is 16.4 kΩ. For a connection through a buffer, for example, the suggested configuration on the ADS1271EVM rating board, the 50 Ω shunt will

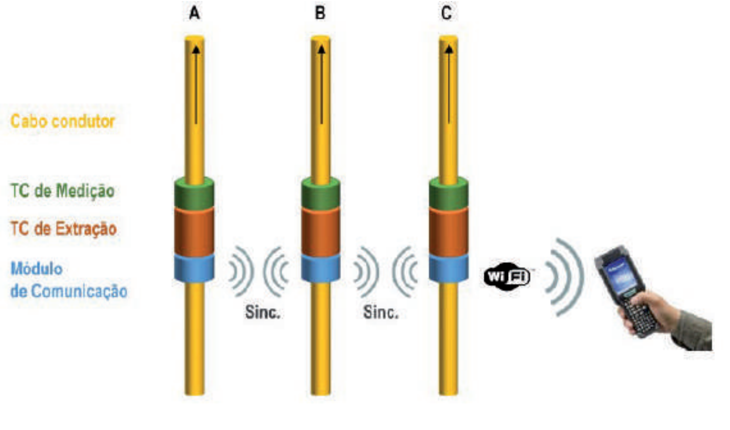


Figure 1.
Concept of application of the wireless and self-powered current transducer.

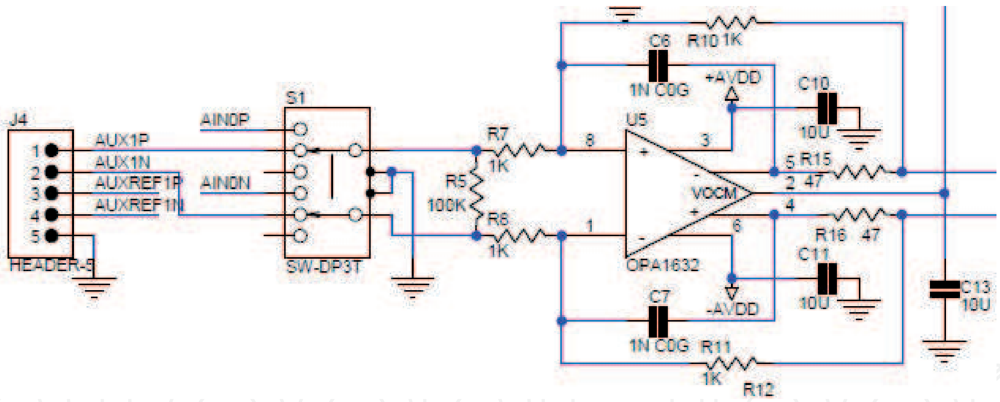


Figure 2.
ADS1271EVM evaluation board input buffer.

be in parallel with the 100 kΩ/2 kΩ arrangement which is about 40 times greater. **Figure 2** presents this arrangement. There are arrangements with a better input impedance, but it is worth remembering that any minor transformation relationship errors arising from the interaction between shunt resistor and input impedance can be compensated by a software in the microcontroller.

2.2 Modeling and simulation of the power extraction CT

An extraction CT can be modeled by the scheme and equation shown in **Figure 3**. As can be perceived, the power in the load, *RL*, depends on the current in the secondary of the CT, I_s, and the current splitter formed by the inductance of magnetization, L_m, and the own load, *RL*. The higher the L_m, the higher is the portion of the current of the secondary that will pass through the load, I_L, and the higher is the power extracted.

In **Figure 3**, by the equation of the magnetization inductance referred to the secondary, $L_{m,s}$, it is perceived that it is proportional to the effective area of its section, A_e, and is inversely proportional to its average length, *D*. On the other hand, the magnetization inductance is also proportional to the square of the number of turns of the secondary, N_2. However, the increase in *N* causes the decrease of the current of the secondary and therefore of the power in the load so that there is an optimum value of *N* for a given configuration. For modeling, a common CT with a bipartite

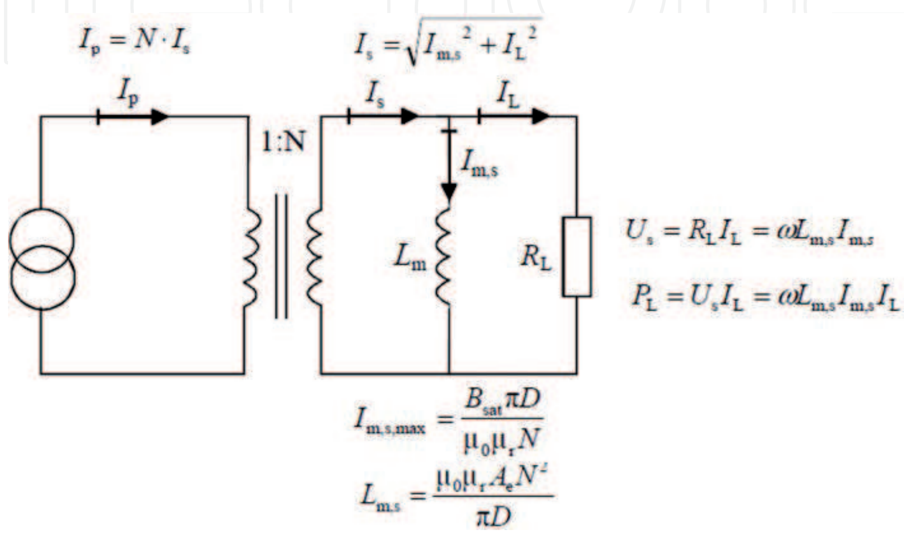


Figure 3.
CT modeling of power extraction, schematic, and equations (toroidal core).

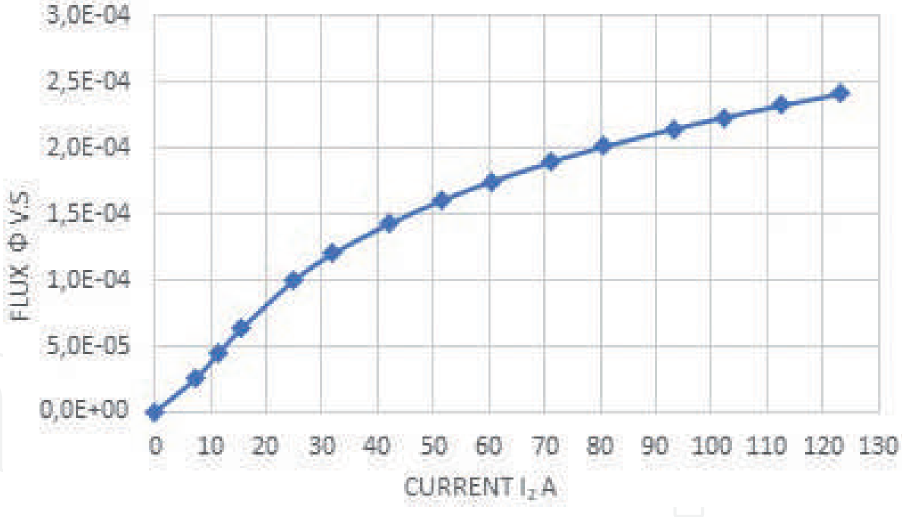


Figure 4.
CT magnetization curve.

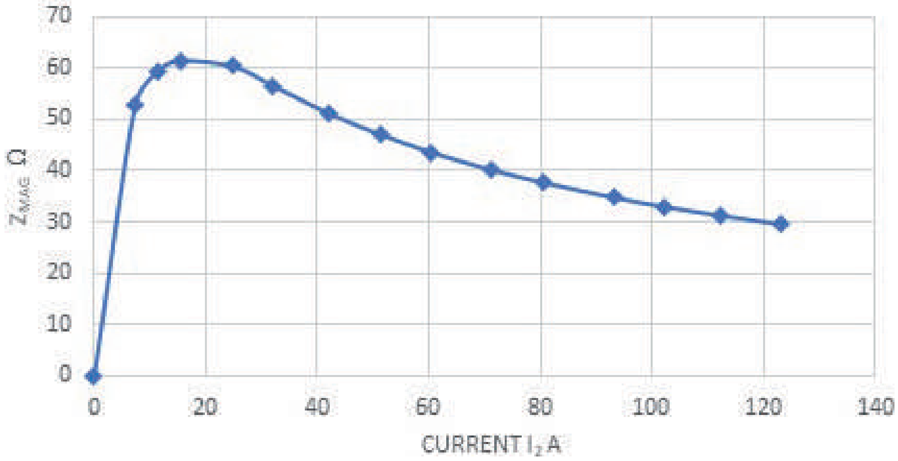


Figure 5.
Behavior of CT magnetization impedance.

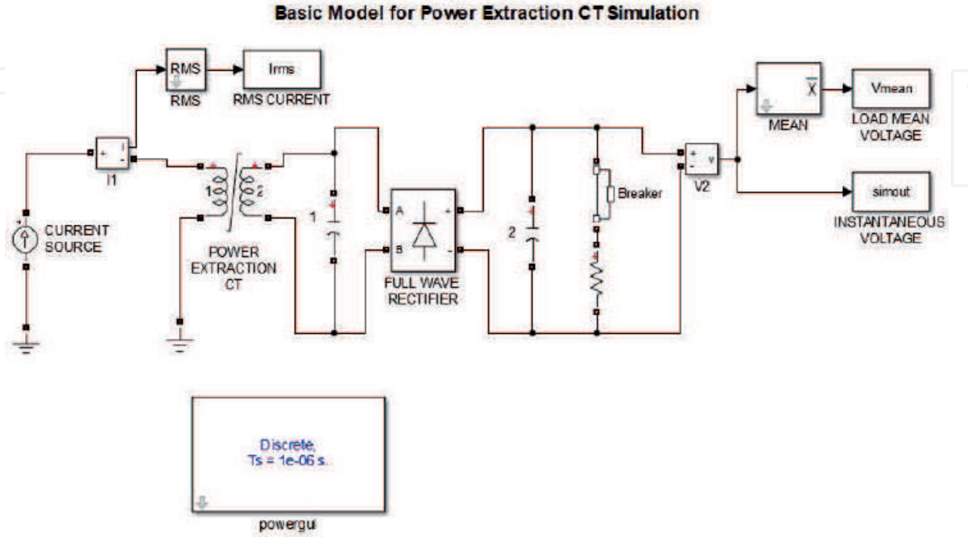


Figure 6.
Model for computational simulation.

silicon steel core is used, presenting an original transformation ratio of 250A:1A, a mass of 411 g (including the original winding), and a nominal area of 128 mm^2.

Figure 4 presents the magnetization curve of the core, separately and together. The tendency of CT with double core saturated with a higher current in the primary is perceived. In any case, according to the estimated currents and measurements in the cable, the CT works far from the core saturation point. It should also be noted that the saturation of the core plays an important role in the aid to the protection of the extractor electronics. **Figure 5** presents the behavior of the magnetization impedance of the test core.

Figure 6 presents the model for computational simulation of the power extraction CT. The transformer block uses the magnetization curve shown above. In this model a CT self-inductance compensation capacitor, a complete wave rectifier to produce a continuous voltage in the load, and a capacitor for voltage "ripple" filtration are included. The resistor has been chosen to be equivalent to the load of the application. It was estimated, previously, that the final prototype would be equivalent to a maximum load of 1.1 W, operating at 5 VDC. This power equates to a resistive load of 22.72 Ω, which was approximated to a load of 25 Ω, for availability, with three 75 Ω resistors in parallel being used.

3. Implementation of the current measurement module

The current measuring module digitalizes the output of the measuring CT and makes it available for processing and transmission. The digital-to-analog conversion is performed by the ADS1271 converter, and its control is performed by the CC3200 microcontroller. The interconnection of the two modules, ADS1271 and CC3200, is presented in the figure below. The set is powered by 5 VDC, and communication between modules is done by the serial peripheral interface (SPI) communication interface.

The CC3200 microcontroller is the master device, and the ADS1271 is the slave device in the SPI communication scheme. The master device provides the clock signal for the SPI interface of the slave device, which sends the data signal (PIN slave out-master in) to the master device. The slave device also sends the data-ready signal to an interrupt line of the master device, interrupting the microcontroller and stating that a valid data is ready for reading and processing.

The power metering module is composed of the magnetic field power extraction CT and the power conditioning circuit. The extraction CT is composed of the core and the winding of the secondary, whose main parameter is the number of turns, which is determined, to extract the estimated power for the application with the minimum current in the primary.

The power conditioning circuit consists of compensating capacitors, a full-wave rectifying bridge, and a DC-DC converter with buck topology, whose main parameter is the output voltage, defined by the power supply voltage of the electronics of the application, in this case 5 VDC. In the buck topology, the output voltage is

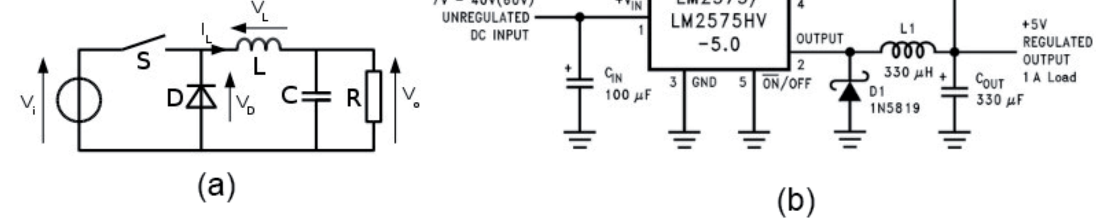


Figure 7.
DC-CC converter with buck topology: (a) overall topology scheme and (b) real circuit with integrated circuit LM2575-5.0.

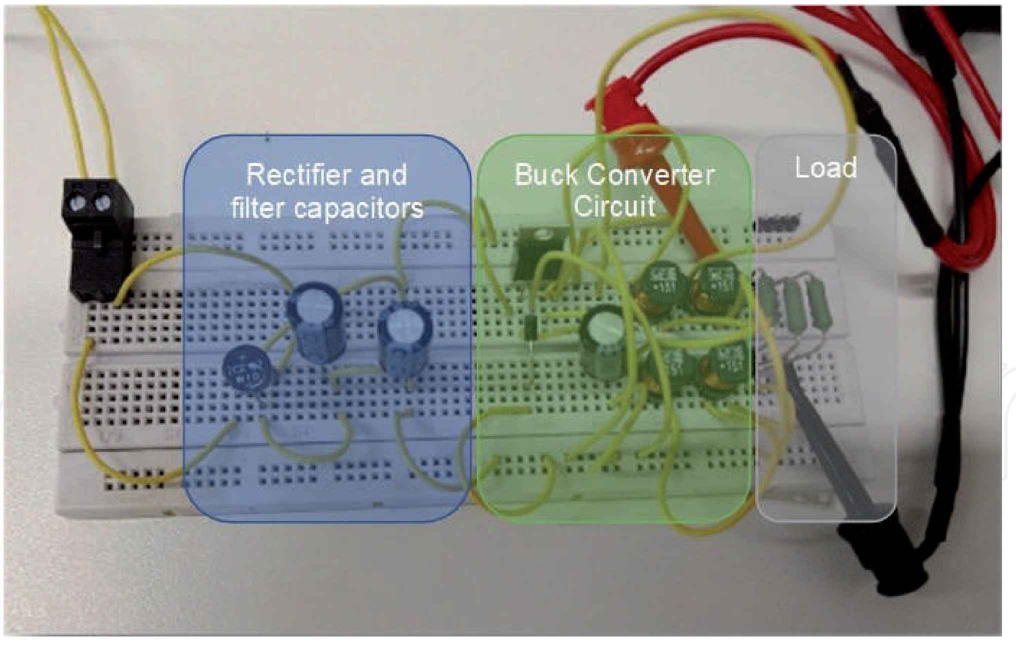


Figure 8.
Protoboard assembly of the buck CC-CC converter circuit, including the rectifier and equivalent resistive load.

less than the input voltage and was chosen according to the voltages obtained at the output of the extraction CT in the range of possible currents for the application.

Figure 7 presents the general schematic of the topology and the schematic of the actual circuit implemented with integrated circuit LM2575-5.0.

Figure 8 introduces the protoboard implementation of the buck converter. In this figure, the rectifier with the ripple filtering capacitors, the buck converter itself, and a resistive load equivalent to the estimated load of the application are shown.

4. Wireless interface specifications

There are a large number of wireless communication technologies for the most diverse purposes. Among these, we can cite three well-known: IEEE 802.15.4 known as Zigbee [9], IEEE 802.11 known as Wi-Fi [8], and IEEE 802.15.1 known as Bluetooth [10].

The IEEE 802.15.4 Standard, Zigbee, is an open standard designed exclusively for use in device networks. It is a technology that does not require much processing or power, being suitable for devices with batteries. The standardization is not yet total so that a device with interface said Zigbee would not necessarily be able to communicate with another device with interface. Since the standard is oriented to device networks, "streaming" applications, which require the continuous submission of data at relatively high rates, are not well attended because the maximum baud rate is 250 Kbps. The range can also be a limiting factor for applications based on this standard.

The IEEE 802.11 Standard, Wi-Fi, is best known and commonly used for connecting devices such as notebooks, tablets, and smartphones to Internet routers. The standard uses radio bands in the range of 2, 4, and 5GHz. It is possible to obtain a "Wi-Fi Certified" certification for a device to ensure its full compatibility with the standard and ensure its interoperability with other devices as well as certificates. This standard is quite suitable for "streaming" applications, being used commonly for audio and video streaming applications, much more demanding, in terms of speed, than the transducer proposed in this project. Data transmission rates of 10 Mbps or larger are common. Another positive point is the long range usually obtained with interfaces of this standard, which can reach 100 m or more.

The IEEE 802.15.1 Standard, Bluetooth and Bluetooth Low Energy (BLE), establishes an interface geared to the transmission of data in short distance, 2–10 m. Streaming applications are serviced very well as long as the distance limitation does not adversely affect the application. The data throughput is between 1 and 3 Mbps. Another limiting factor is the limit of seven devices on a Bluetooth network. The Bluetooth standard is well controlled, and every device needs to be certified to use the name.

Thus, considering the general characteristics of these three wireless interface standards, the IEEE 802.11 Standard, Wi-Fi, shows the most indicated, taking into account the general requirements of this application, which are range, greater than 10 m; data transmission rate, in the order of Mbps; and practicality and integration facilitated with the communication network of the plant.

The two most common and known transport layer protocols are transmission control protocol (TCP) and user datagram protocol (UDP). The CTP is one of the main protocols of the Internet protocol set. It enables reliable, orderly, and error-checking packet transmission. The UDP uses a simpler, connectionless communication model. UDP checks the integrity of the data with "checksum" and uses a system of several ports for different functions, both in the target and in the source. There are no handshake dialogs between the source and the destination because there is no established connection. Therefore, there is no guarantee of delivery of packages. Thus, the UDP is suitable for applications where the integrity and correctness of the data are not necessary or can be done in the application itself, avoiding the cost of this processing in the protocol stack. In general, real-time applications that privilege speed use UDP, as it is preferable to lose a package waiting for a delayed package. In the "streaming" data-type applications, the first transport protocol option is UDP.

The application of this device is related to the monitoring of engine condition, and the condition of a motor changes slowly, at least in the parameters of interest. Therefore, if there is a loss of a package compromising a measurement, another measurement can be requested without prejudice to the monitoring. Besides, it is more appropriate for data integrity checking to be done on the target computer, which probably has more processing capacity than the application microcontroller.

The hardware of the prototype Wi-Fi communication interface module consists of the CC3200-LaunchXL card. This board is composed of circuits for the use of external peripherals of the CC3200 microcontroller, circuits for debugging functionalities, and the antenna of the wireless communication system itself.

The CC3200 is a single-chip microcontroller with integrated Wi-Fi connectivity for the Internet of Things applications. Its core consists of an ARM Cortex-M4 processor that allows the implementation of applications with processing and wireless communication interface with a single integrated circuit.

Provisioning on Wi-Fi-type wireless networks is the process of connecting a new Wi-Fi device (called a station) to a Wi-Fi network (called a hotspot). The provisioning process involves loading the station with the network name (called SSID) and the security credentials. The Wi-Fi security standard distinguishes between personal security, for home and business use, and business security, for use in large offices and large networks. In the case of the enterprise security standard, certificates are installed that are used to verify the health of the station and the network by interacting with a secure server managed by the IT department. In the case of the personal security standard, only the use of a password is required.

In the case of CC3200 devices with the SimpleLink application programming interface (API), there are three provisioning methods: SmarConfig, AP mode, and Wi-Fi protected setup (WPS).

The SmarConfig Technology owns the Texas Instruments and consists of a provisioning method for non-peripheral input/output devices (keyboards, mice,

```c
long WlanConnect()
{
    SlSecParams_t secParams = {0};
    long lRetVal = 0;

    secParams.Key = (signed char*)SECURITY_KEY;
    secParams.KeyLen = strlen(SECURITY_KEY);
    secParams.Type = SECURITY_TYPE;

    lRetVal = sl_WlanConnect((signed char*)SSID_NAME, strlen(SSID_NAME), 0, &secParams, 0);
    ASSERT_ON_ERROR(lRetVal);

    // Wait for WLAN Event
    while((!IS_CONNECTED(g_ulStatus)) || (!IS_IP_ACQUIRED(g_ulStatus)))
    {
        // Toggle LEDs to Indicate Connection Progress
        GPIO_IF_LedOff(MCU_IP_ALLOC_IND);
        MAP_UtilsDelay(800000);
        GPIO_IF_LedOn(MCU_IP_ALLOC_IND);
        MAP_UtilsDelay(800000);
    }

    return SUCCESS;

}
```

Figure 9.
C code using the SimpleLinkK API to connect to the provisioned Wi-Fi network.

monitors, and CT), as is the case with the application of this project. This method uses an application to broadcast network credentials through a smartphone, tablet, or PC to a Wi-Fi device that has not yet been provisioned.

When the unprovisioned device uses the SmartConfig mode, it enters a special scanning mode, hoping to collect the network information being broadcast by the SmartConfig application on a smartphone, for example. The smartphone needs to be connected to a Wi-Fi network to broadcast its credentials.

The access point (AP) method is the most widespread method for provisioning non-peripheral input/output devices over Wi-Fi networks. In this method, the unprovisioned device starts in access point mode, creating its network with SSIDs and credentials set by the application's manufacturer, so a smartphone or PC can connect directly to the unprovisioned device and configure your provisioning on the desired network. These elements are the provisioning method adopted in the final version of the CT.

The Wi-Fi protected setup (WPS) method is the only industry standard available for provisioning non-peripheral input/output devices. It was introduced by the Wi-Fi Alliance in 2006 and is a safe and easy method of provisioning devices without knowing the SSID of the network or long typing passwords. The default defines two mandatory methods for access points with WPS: using personal identification number (PIN) and using a push-button-connect (PBC).

Once the SSID and the access credentials have been established, the code, shown in **Figure 9**, makes the connection to the chosen network using the SimpleLink application programming interface (API) in C code.

The basic flow of connecting, transmitting, and receiving data with a UDP socket from the SimpleLink application programming interface (API) of the CC3200 microcontroller in C language is presented next to the client and server side.

On the client side, you first create a socket of the IPv4 type and select a UDP connection, as follows:

```c
int SockID;
SockID = sl_Socket(SL_AF_INET, SL_SOCK_DGRAM, 0);
```

In the code above, the first parameter, SL_AF_INET, indicates the selection of an IPv4 socket; the second parameter, SL_SOCK_DGRAM, selects the UDP protocol; the third parameter, 0, selects the protocol default mode; and the SockID variable is the handler for the socket that will be used in all subsequent operations. The parameters used above and others are established in the header file "socket. h."

Because UDP is a connectionless protocol, the client can begin sending data to a specific address without verifying that the device is active or not. The following code is an example of how to do this:

```
#define IP_ADDR          0xc0a80164
#define PORT_NUM         5001

Addr.sin_family      = SL_AF_INET;
Addr.sin_port        = sl_Htons((UINT16)PORT_NUM);
Addr.sin_addr.s_addr = sl_Htonl((UINT32)IP_ADDR);

Status = sl_SendTo(SockID, uBuf.BsdBuf, BUF_SIZE, 0,   (SlSockAddr_t *) &Addr,
sizeof(SlSockAddrIn_t));
```

In the code above, IP_ADDR is the IP address in hexadecimal format, PORT_NUM is the port number used, and Addr is a structure that gathers all the necessary information (user-specified information and other standard information) to the operation.

Finally, to close the socket, you use the following function:

```
sl_Close(SockID);
```

On the server side, the creation of the socket is identical to the client side:

```
SockID = sl_Socket(SL_AF_INET,SL_SOCK_DGRAM, 0);
```

The socket then needs to be bound to the local IP address through the sl_Bind function:

```
#define PORT_NUM        5001

SlSockAddrIn_t  LocalAddr;
AddrSize = sizeof(SlSockAddrIn_t);

TestBufLen  = BUF_SIZE;

LocalAddr.sin_family      = SL_AF_INET;
LocalAddr.sin_port        = sl_Htons((UINT16) PORT_NUM);
LocalAddr.sin_addr.s_addr = 0;
Status = sl_Bind(SockID,  (SlSockAddr_t *) &LocalAddr, AddrSize);
```

From this point, you can try to receive data by the socket of the source specified by Addr, the fifth parameter of sl_RecvFrom:

```
#define BUF_SIZE 1400
SlSockAddrIn_t  Addr;
char            RecvBuf[BUF_SIZE];

Status = sl_RecvFrom(SockID, RecvBuf, BUF_SIZE, 0, (SlSockAddr_t *) &Addr, (SlSocklen_t*)
&AddrSize );
```

If the "nonblocking" option was not specified, the command is locked until the amount of data specified in BUF_SIZE is received.

To close the socket, use the sl_Close function as before:

```
sl_Close(SockID);
```

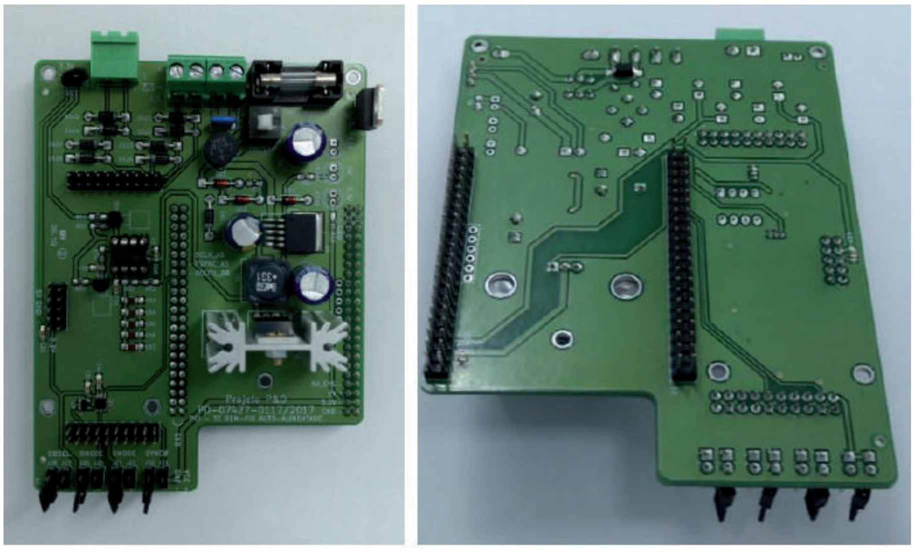
5. Assembly of the current transducer

The produced prototype boards are presented in **Figures 10** and **11**.

An enclosure was designed with a more rounded and nicer shape visually. The 3D design can be seen in **Figure 12**.

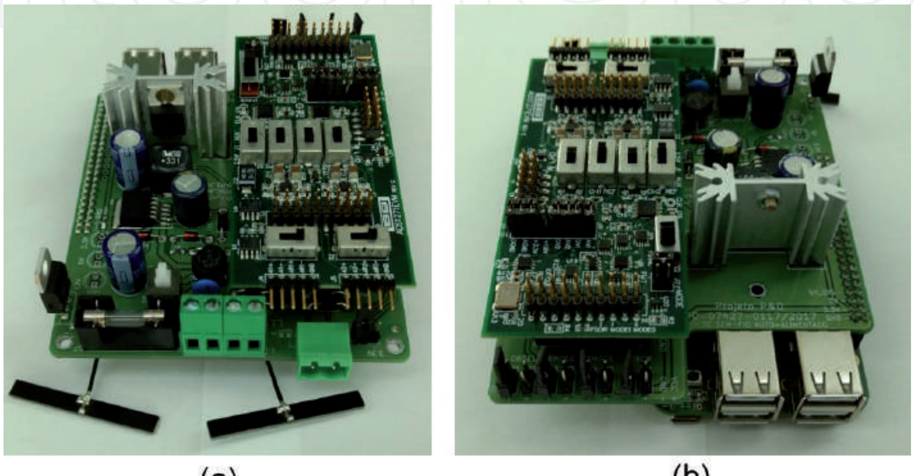
The enclosure design was executed in Delrin® Resin, conferring resistance and robustness to the prototype. **Figures 13–15** show the prototype in its final enclosure.

Figure 16 below presents the operation flow chart for the prototype device. Once the wireless self-supplied module is installed around the motor cable and there is enough current to drive the power conditioning circuit, a timer starts to count. After a stabilization time, the available power is supplied to the main application modules: microprocessor, wireless interface, and analog-to-digital converter. After that, a Wi-Fi network is created for provisioning, as described in Section 4, or direct connection, if desired. Once the device is connected to the desired Wi-Fi network, it can receive commands from the main software or execute operations according to a setup schedule.



(a) (b)

Figure 10.
Device board: (a) top view and (b) bottom view.



(a) (b)

Figure 11.
Board of the device mounted with the SBC and ADS1271-EVM board: (a) front view and (b) rear view.

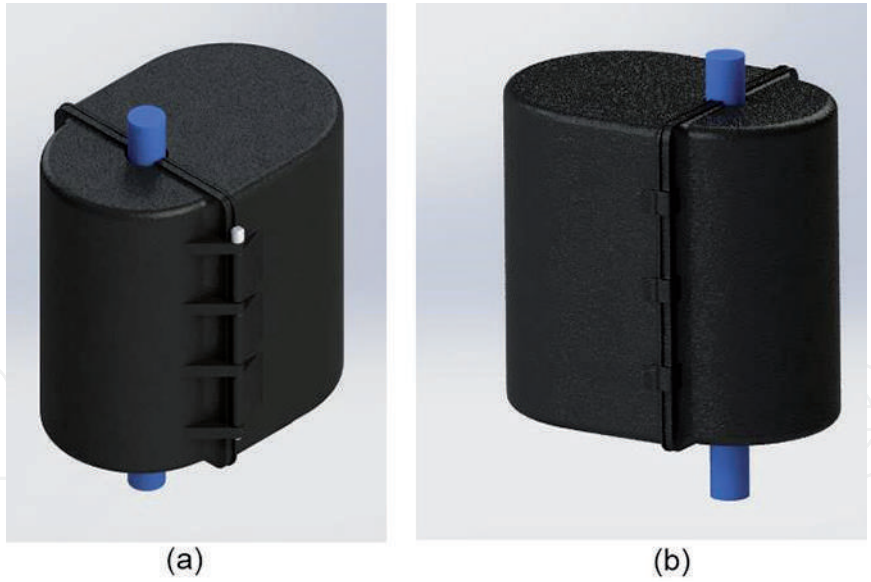


Figure 12.
3D design of the device enclosure.

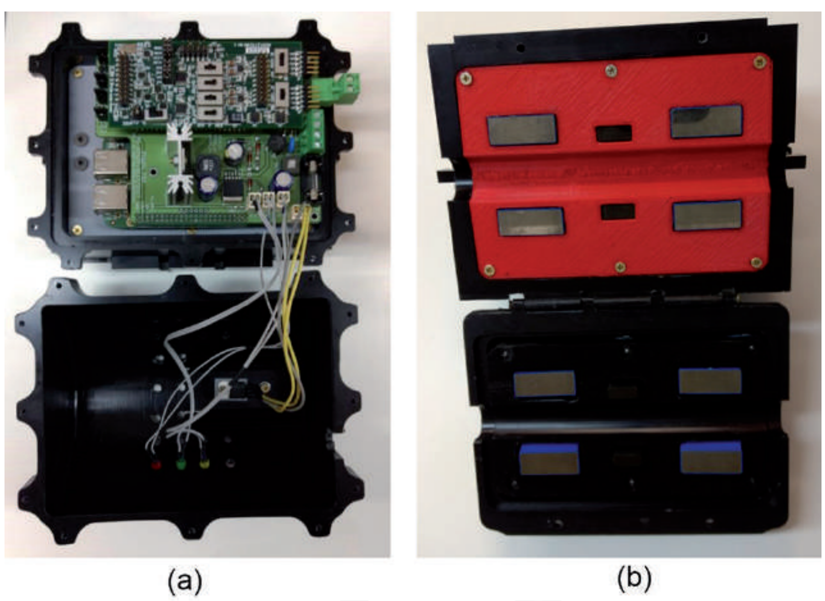


Figure 13.
The open device enclosure exposing (a) the electronics and (b) the CTs for measuring and extracting power.

Figure 14.
Front view of the device.

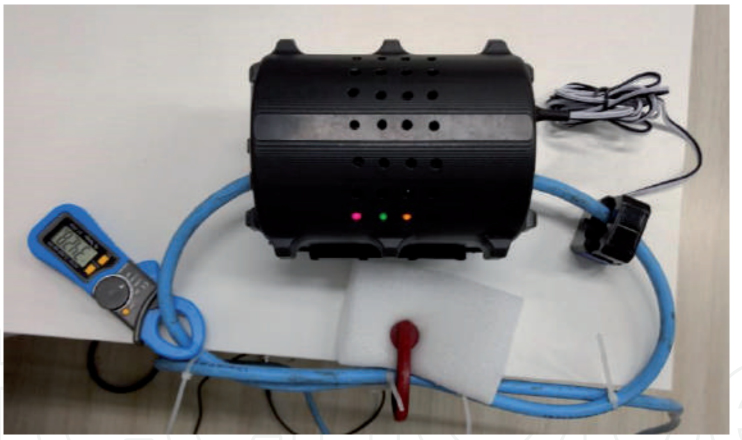


Figure 15.
Device operating in a test setup with 34 a current.

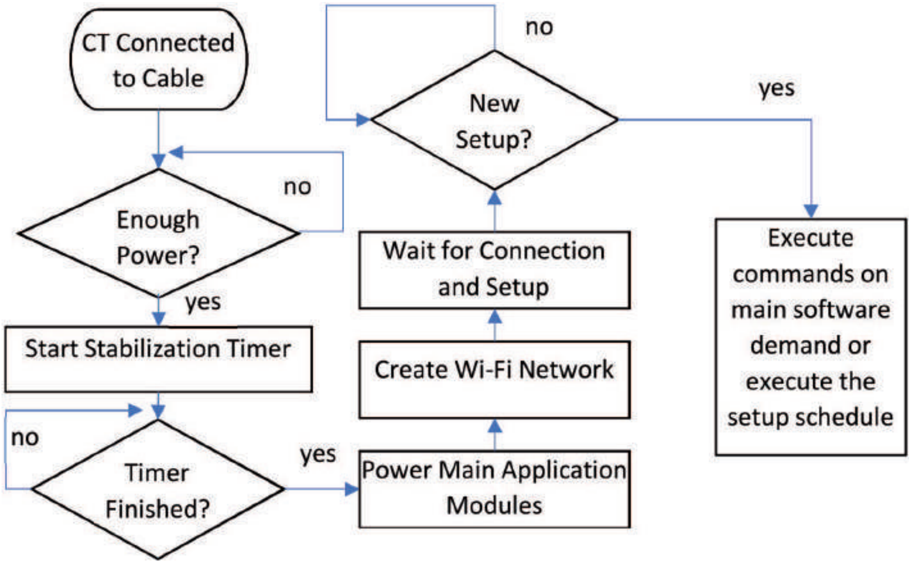


Figure 16.
Operation flowchart for the wireless self-supplied current transducer.

6. Results of tests

6.1 Tests in the laboratory

The objective of these tests was to simulate the actual operating conditions that the device will face when installing on the electric motors in the field. For example, in the case of off-road vehicle (ORV) motors (speed regulator), the prototype must:

- Support the starting condition offered by the "soft-starter" system.
- Work, most of the time, with the current in "no load" (30–60 A).
- Withstand the operating current of the motor (about 162 A), which lasts about 1 min.

Also, for the case of motors without soft starter, the condition of direct starting with currents of the order of six times the nominal current has been tested. For this, a motor of 2.1 A was used, and the cable was passed through one of the phases by the prototype 18 times, producing a motive magnet force of about 36 At in normal

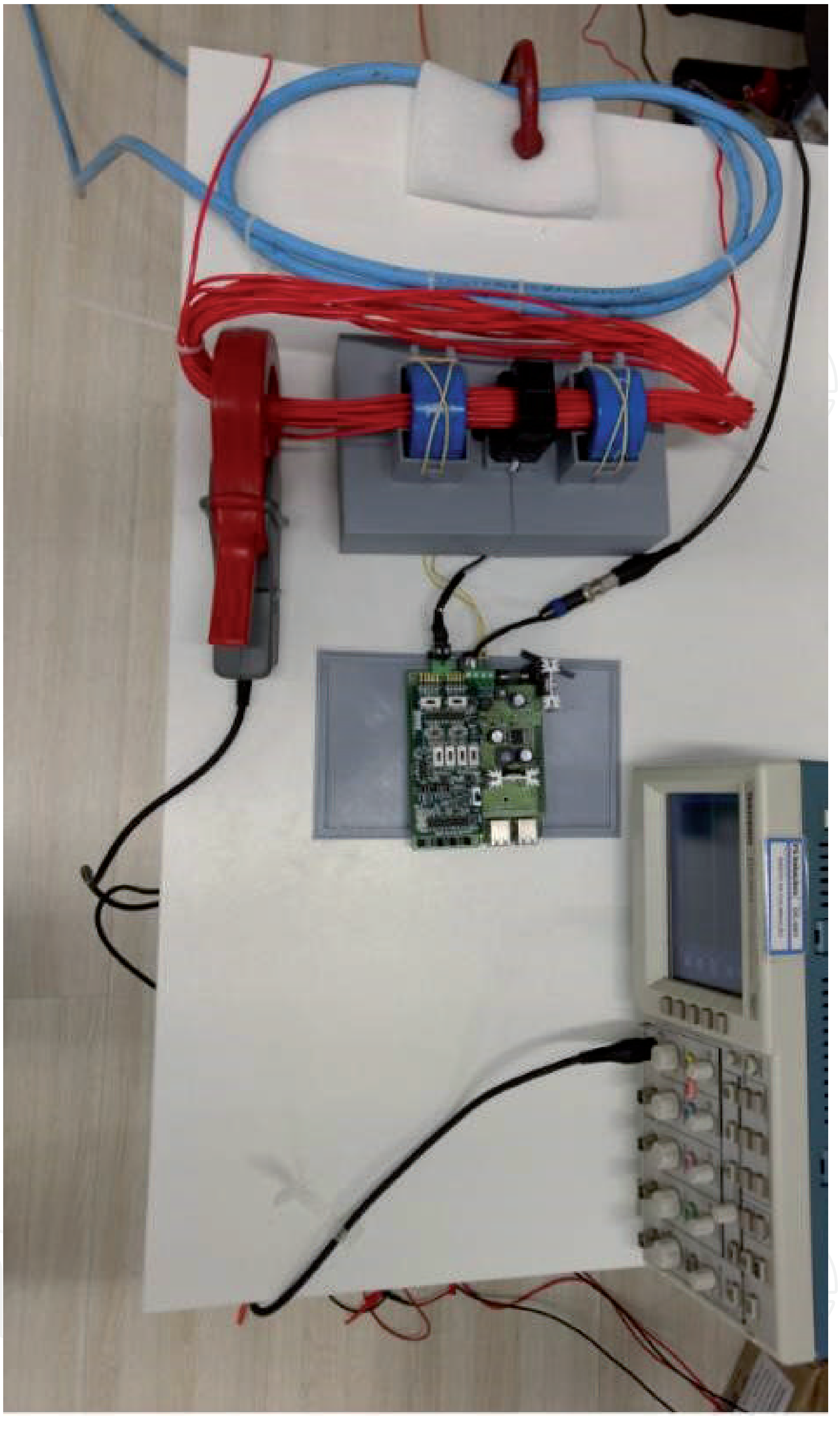


Figure 17.
Assembly of the starter test for motor without soft starter.

condition and 243 At in the starting condition. The assembly for the simulation of the starting situation is presented in **Figure 17**; meanwhile, the starting curve of the motor is displayed in **Figure 18**.

The main points verified were:

- Prototype stability for operation and communication in the presence of available minimum currents

- Stability of overvoltage protection in the presence of maximum available currents

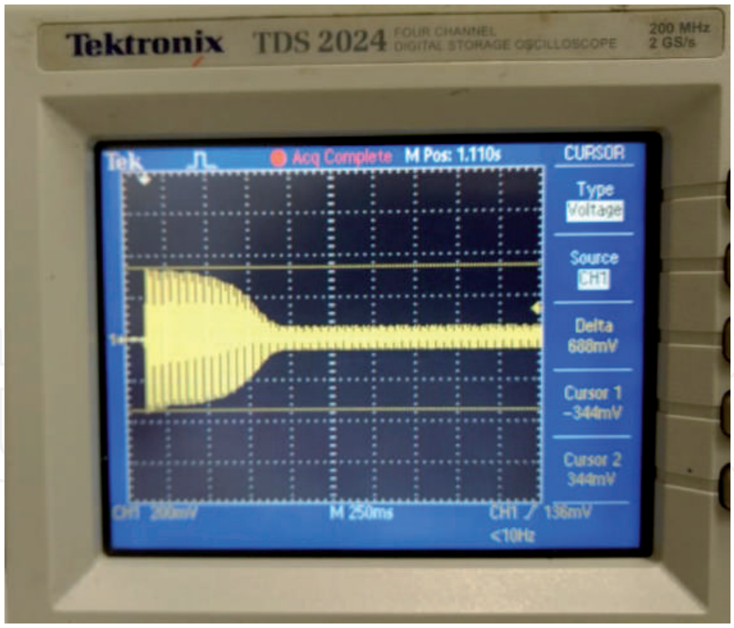


Figure 18.
Engine starting test indicating that the starting current reached about 344 to peak (243 Arms)—the ratio of the current transducer equal to 1 MV/a.

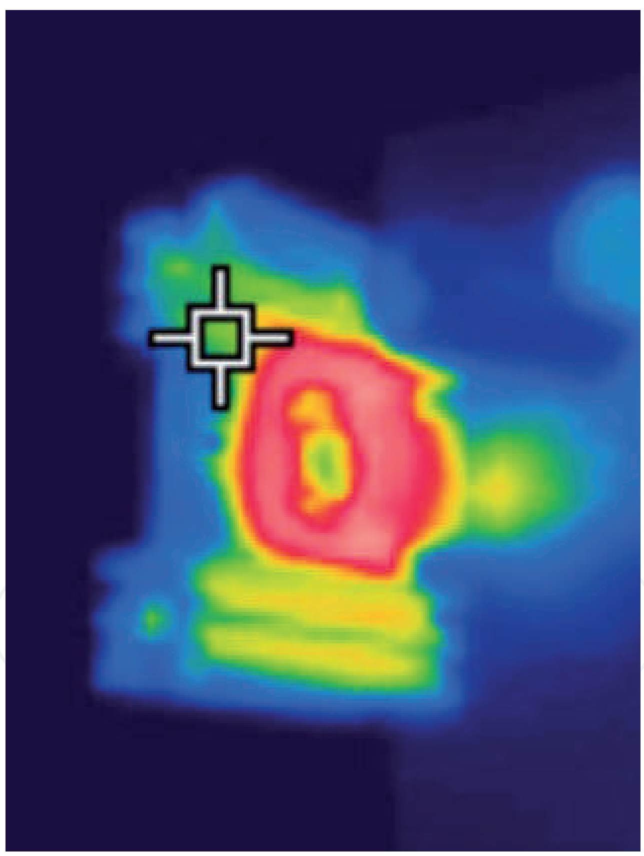


Figure 19.
About 79°C at the hottest point (set operating above the nominal for 4 min).

During the tests, the main subsystem verified was the protection circuit of the buck converter, which prevents the input voltage from being greater than the allowable limit, 40 VDC. In this case, the protection is specified to reap the voltage at about 36 Vcc, keeping the application running and dissipating surplus energy in the protection transistor buffer. The temperature of the transistor/heat sink assembly was monitored with the extractor operating with a current of 170 A (greater than the operation of about 162 A) over 4 min that is four times longer than the operating period reported in this condition, as shown in **Figure 19**. The system operated normally, and the maximum temperature in the set reached 79°C.

6.2 Operation at the Pimental hydraulic power plant

Figure 20 presents the device installed and operating in the motor BB-ORV101, at Pimental hydraulic power plant, in Altamira, north of Brazil.

The prototype proved to be stable from a minimum current of about 34 A, as presented in **Figure 21**.

According to field measurements, the BB-ORV motors operate for about 1 min in current slightly higher than the nominal board. This condition was measured and presented in **Figure 22**.

Figure 20.
Device installed at Pimental hydraulic power plant in Brazil.

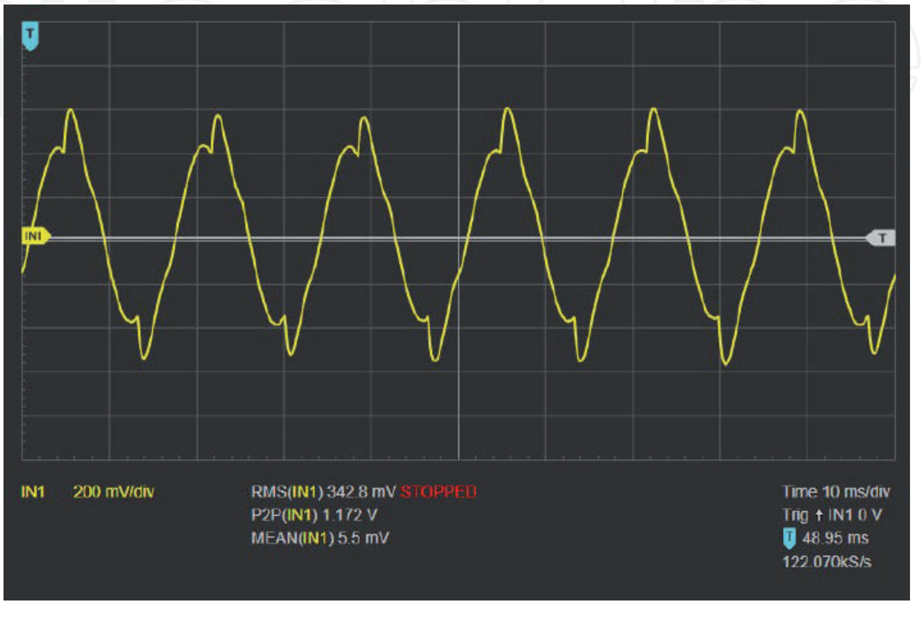


Figure 21.
Waveform presented by the oscilloscope in the current condition of minimum, 34 A.

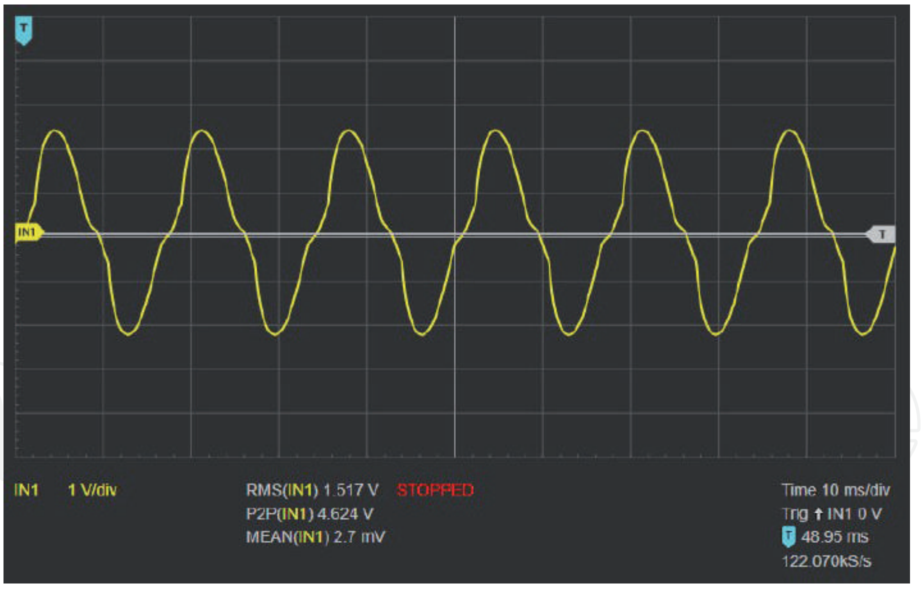


Figure 22.
Waveform presented by the oscilloscope in the current condition near the nominal, 149 A.

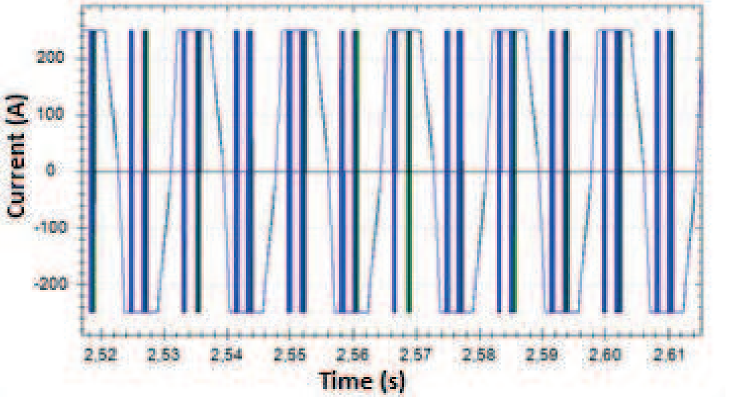


Figure 23.
Saturated and distorted waveform presented by the prototype in the condition of starting current, 602 A.

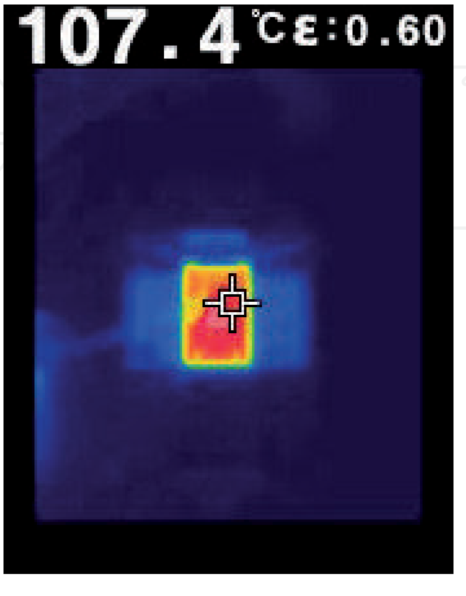


Figure 24.
Thermal image of the transistor/protection sink of the buck converter, in the condition of starting current, 602 A, after about 60 s of operation.

In the field measurements, it was found that in the BB-ORV motors, which have a soft-starter device, the starting condition takes about 4 s and reaches a current of 400 A. To introduce a safety factor, the prototype was subjected to currents of 600 A for more than 60 s. The objective is not that the prototype can measure these currents, as they are far above the nominal CT, which is 200 A but can withstand them without fail. Therefore, it is normal, in this condition, that the prototype displays saturated or distorted currents, as shown in **Figure 23**. **Figure 24** shows the thermal image of the transistor/protection sink of the buck converter, in the condition of starting current, 602 A, after about 60 s of operation.

6.3 Considerations about the power harvesting capability of the prototype

The power harvesting capability of the prototype reaches 2.5 W in the condition of a minimum current of 34 A in the measured cable. This power suffices to drive a single-board computer based on an ARM microprocessor with 64 bit architecture, 1 GHz clock, 512 Mb RAM, Linux operating system, and many peripherals. Such a system is able to perform many digital signal processing (DSP) techniques in the electric current signals acquired from the monitored electric motor, for motor monitoring applications do not require a real-time processing, since a few signals a day suffice for a condition diagnostics of the slow developing faults that can be monitored by the current spectral analysis technique.

7. Conclusions

This chapter aims to show the development and implementation of an innovative current transducer inserted in the context exposed above, i.e., dynamic current measurement (waveform) or its RMS value, for the purpose of monitoring the energy and/or monitoring the condition of assets; wireless interface with remote viewing and/or recording device, self-powered by the magnetic field of the current measure, without connection to the electrical system through external sources and power cords; and ability to synchronize with other gauges or use a real-time base, allowing the correlation of the measurements of various transducers in the same time base.

The main objective of this chapter was to present the development of a current transducer with wireless data transmission self-supplied by the magnetic field of the transduced current. The proposed measuring device involves the cable, whose current is intended to be measured, extracting power from the magnetic field around the conductor to feed the current transducer itself and the data flow generator circuit of the measured current ("streaming") through a wireless transmission protocol. The measured current can be viewed on a handheld device such as a "smartphone" or data collector, for example. The extracted signal was used to monitor the condition of the cooling system motors of the Pimental hydraulic power plant through the analysis of the electrical signature analysis.

The main advantages of the proposed system are:

- Ease of installation: the device involves the cable whose current is to be measured.
- Easy access to data: wireless and remote interface with data collectors or "smartphones."

- Nonintrusive: the only interface with the system to be measured is the magnetic field, and there will be no sources or cables interfering with the electrical panels of the plant.

- Record of the data in the "cloud" if desirable.

- Ease of implementation of energy monitoring and condition-based maintenance applications.

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Author details

Erik Leandro Bonaldi[1], Levy Ely de Lacerda de Oliveira[1], Germano Lambert-Torres[1*], Luiz Eduardo Borges da Silva[2] and Vitor Almeida Bernardes[3]

1 Itajuba Federal University, Brazil

2 Gnarus Institute, Brazil

3 Norte Energia, Altamira, Brazil

*Address all correspondence to: germanoltorres@gmail.com

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Chapter

How the Data Provided by IIoT Are Utilized in Enterprise Resource Planning: A Multiple-Case Study of Three Change Projects

Jyri Rajamäki and Petra Tuppela

Abstract

An extreme increase in data production has taken place over the past few decades with a large number of sensor and smart devices acquired from distributed data sources. Industrial Internet of Things (IIoT) enables seamless processing of information by integrating physical and digital world devices that can be used ubiquitously. This multiple-case study analyzes how the data generated by the IIoT benefit enterprise resource planning. In the analyzed cases, IIoT has been produced using and integrating various digital services and software in the enterprise. Data produced by IIoT might be raw data or pre-analyzed by the IIoT service provider according to the enterprise's needs. Services based on IIoT solutions ensure competitiveness within the enterprise since IIoT is flexible and easy to apply on future demands. IIoT generates increased amount of data and enterprises can utilize it to provide significant benefits to their operations. The cross-case conclusions emphasize that improving operational processes with data does not provide maximal benefit to the enterprise. Data-driven procedure and the entire change project (digital transformation) together with new procedures will provide most benefits to the enterprise.

Keywords: multiple-case study, digital transformations, change project, industrial internet of things, enterprise resource planning

1. Introduction

An emergent number of enterprises are deploying new solutions utilizing Industrial Internet of Things (IIoT). IIoT solutions provide many benefits to an enterprise, but they also drive the enterprise to redesign its operations to data-driven processes. On the other hand, the solution adjusts the enterprise's services to make them more profitable and precise. This requires the enterprise to make strategic but also organizational changes in order to succeed in the change [1]. During the development process, enterprises brainstorm, generate ideas, compare and test IIoT solutions for later changing the business model. The services provided by IIoT require not only an IT competence developer but also competence in business activity insight and expertise. IIoT solutions also affect sales, marketing, and mostly development of service concepts. In some cases, IIoT can be the base of a new service concept or a total digital transformation process.

Change, derived from IIoT solution, requires time in every organization. Change includes planning, deployment, and implementation of current solution. In some cases, the Industrial Internet can affect the enterprise's whole strategy by remodeling or modifying its operations. IIoT solution may even influence value proposition since data drive the operations and accurate data provide new possibilities in daily business. Due to technical solution that collects data, new information is created. Therefore data can even have an impact on enterprise management tools; using of data driven management tools to assess processes [1].

This chapter presents a multiple-case study research (MCSR) of three change projects in which new IIoT solutions have been put into operations in three different Finnish enterprises. The research questions are:

- How and when the enterprise recognizes the changes required by applying the new IIoT solution?
- How the enterprise applies the new data provided by the IIoT solution?
- Why the change is crucial, and how the whole organization succeeded in implementing the change?

The chapter follows a linear-analytic structure of the sequence of subtopics involving the issue being studied, the methods used, a review of the relevant literature, the findings from the collected and analyzed data, and conclusions and implications from the findings. After the introduction, Section 2 proposes a used methodology of the deliverable. Section 3 handles the theory and how it has been built. Section 4 presents the individual case study analysis. Section 5 includes cross-case study conclusions and concludes the chapter.

2. Research approach

Figure 1 shows how the MCSR approach is applied in this research. The initial step in designing a MCSR consists of theory development (see Section 3), and the next steps are case selection and definition of specific measures in the design and data collection process. Each individual case study consists of a whole study, and

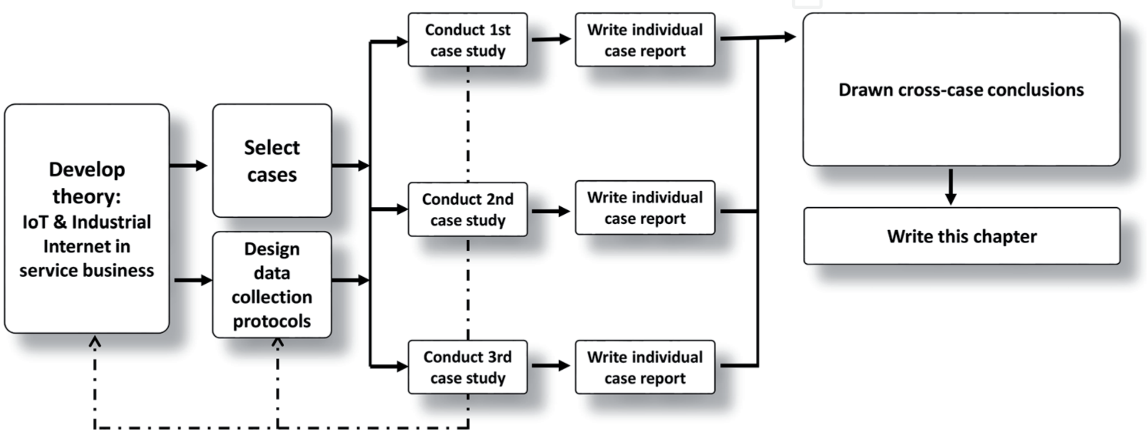

Figure 1.
Applied multiple-case study approach.

then conclusions of each case are considered to be the replication by other individual cases. Both the individual case and the multiple result should be the focus of a summary report. For each individual case, the report should indicate how and why a particular result is demonstrated. Across cases, the report should present the extent of replication logic, including certain and contrasting results [2].

Any use of multiple-case design should follow a replication, not a sampling logic, and choosing of each case should be made carefully [2]. In **Figure 1**, the dashed-line feedback represents a discovery situation, where one of the cases does not suit the original multiple-case study design. Such a discovery implies a need to reconsider the original theoretical propositions. At this point, redesign should take place before proceeding further, and in this view, the replication approach represents a way of generalizing that uses a type of test called falsification or refutation, which is the possibility that a theory or hypothesis may be proven wrong or falsified [3]. This MCSR consists of three individual case studies presented in Section 4. The sources of evidence used in the individual case studies consist of documentation, archival records, interviews of enterprises' top management and IIoT solutions suppliers, direct observations, participant-observation, and physical artifacts. The data are retrieved in a specific time period (cross-sectional), the largest part of the data is qualitative (empirical) and involves purposive sampling and a specific selection of a phenomenon (case studies). Every individual case study was reported separately to the top management of the enterprise in question. Cross-case conclusions were carried out via a document analysis exercise.

3. Industrial Internet of Things in service business

The Internet of Things (IoT) refers to a system of smart devices connected to each other through the Internet [4]. These things include technology that enables them to communicate, sense and interaction with internal space as well as external environment. In other words, physical things can collect data, be connected to other things, and share data. These things can be sensors, smartphones, smartwatches, computers, and home and industrial appliances—anything that can collect, handle, and send data for forward treatment and analyses. First, IoT systems were consumer-centric, but the disruptive nature of this technology has enabled the adoption of IoT technology in a gamut of industrial settings, thus leading to the development of Industrial Internet of Things (IIoT) technology [5]. Technology enables new success stories in every business industry. The true success factors, in order to succeed in IIoT solution implementations, are people in enterprises, processes, and context.

Data alone that are provided by IIoT solutions are not of any value. The collected data connected to business unit's context or other sources of data provide the valuable benefits. Data can be used to understand challenges better or to enhance processes. Collected data may even support management in decision-making process.

By purchasing IIoT solutions, enterprises maintain their competitive advantage. The solution would respond quickly for future spontaneous and accurate demands since things are connected to network and therefore can be updated online. Services can be adjusted both due to competition, commercial, and also to legislation requirements. IIoT solutions mostly include technology, network, and software. In addition, they are always designed for enterprises' needs and desires. IIoT solutions are custom-made and they are to be integrated into the enterprise's existing systems. Data can be provided as raw data, pre-analyzed, or expressed in visual dashboards.

Since the experimental period of IIoT solutions has been exceeded in the past few years, companies are today seeking sustainable solutions to support their operational processes and bringing real value to the company. The technology behind the solution has been proved to operate as it should which means that the expected data can be provided by it and it is accurate. The price of sensors and detectors has been decreasing, which means that enterprises' investment of the technology solutions covers only project and implementation costs. In addition, data storage and several cloud services are available at reasonable price. Low maintenance costs encourage companies to store data for further need.

There are several data strategies that companies can apply data provided by IIoT solutions. Companies can collect data in order to use it to support and enhance their own operational process and business activity. Data can be used not only to guide operations but also show real-time data. These are valuable in enterprises' daily operations. Data can be used to prevent unnecessary actions, the so-called fire situations. In optimal conditions, the data are used to forecast and control actions before they turn into these fire tasks.

For creating business model around Industrial Internet fundamental, there are five key elements:

1. Value creation in service network

2. Building and developing global service network

3. Customer-centric and cost-efficient service process planning

4. Creating positive customer experience

5. Inventing profitable revenue generation logic

When designing a new business model that is based on IIoT, enterprises can use these elements to base it on. This encourages enterprises to place customers and services in the center in order to not only gain higher customer satisfaction but also increase sales in service. These elements can also be applied to develop business activities and generate profitable core or supporting functions.

Because the amount of data grows at an unprecedented scale and depth with the proliferation of smart and sensor devices, big data analytics has emerged as a key initiative in the IIoT field [6–8]. Recently, artificial intelligence (AI) has become a key factor in big data analytics in industrial applications [9].

4. Empirical cases

This section briefly describes the three empirical cases that belong to this multiple-case study analysis. The individual case reports were published earlier, but this section summarizes their main research results with regard to this MCSR.

4.1 Case I: OnniBus.com

OnniBus.com (later OnniBus) started their transportation business at 2012. Within few years, they have managed to grow their business to one of the largest brands in Finland. OnniBus has disrupted mass transportation with competitive, rather low, pricing. Today, they move customers frequently in the most popular routes and also daily all around Finland with their 128 buses. About 28 million kilometers are bring customers from one city to another. With Telia Connected Vehicle solution, OnniBus primarily seeks savings in costs.

OnniBus among others is the first transportation company that applied the Telia Connected Vehicle solution. This solution monitors ground vehicles in action and it optimizes the operation of hardware by using real-time data installed in the vehicles. In addition, the solution enables combining different services that beforehand were provided to OnniBus from different service providers. When considering the bus driver, it also takes much less effort to follow only one screen rather than several.

In the early phase, Telia's solution was installed in all 68 double-decker buses and later in the 60 single-storey buses. The service requires that the driver of the bus logs into the vehicle system with an identifying digital card, which is a very secure way to log in. In the past, drivers did not always remember to sign in and no data could be obtained at that time. OnniBus uses Telia's solution to remotely read digital plotters and cards. They are able to monitor remotely that driving times are being realized and digital cards are always being used by drivers. This kind of data is a very powerful management tool. The CEO of OnniBus Lauri Helke sums up "what you don't measure, you can't lead." In order to motivate drivers to drive more ecologically, OnniBus started to publish driver-specific results to the staff every month. Such transparent information encourages everyone in the company to see what kind of data can be achieved with financial driving.

In order for OnniBus to achieve savings in costs, the most important thing about implementing this service is to report about OnniBus driver habits and fuel consumption per driver. Only the fuel savings from the data generated by Connected Vehicle-solution will be 1–5% annually. In double-decker buses alone, OnniBus consumes approximately 5.5 million liters of fuel per year, which means a fuel cost of EUR 6 million. This saving as such is significant. Since Telia's solution also monitors the vehicles, there are savings directly on tire costs and other vehicle operating costs. In addition, it provides an ecofriendly approach to bus transportation business.

4.2 Case II: Pohjolan liikenne

Transportation industries are under critical inspection since the environmental cause. In order to utilize different sources of data and manage with data, companies can achieve massive advancements by how they optimize their actions. Focusing on fuel economy and improving effective fuel consumption are significant ecologically friendly approaches in the transportation industry and furthermore companies reserve in costs.

Oy Pohjolan Liikenne Ab (later Pohjolan Liikenne) has been serving in the transportation industry since 1949. They offer transportation services in commuter traffic, country traffic, local transportation, metropolitan area, order and contract driving as well as Finnair CityBus traffic driving.

Telia's solution means that bus vehicle's actions are being monitored and optimized according to real-time data. Cost-efficient driving and measurement have been challenging before but since the new solution provides data real time, information can be used proactively. Despite that, the savings in fuel are concrete. With that said, data from consumption of fuel are precise and therefore the company has been able to seek the best-practice driving mode for drivers. With Telia's solution, Pohjolan Liikenne can react to drivers' driving habits in real time. Along with the service, Pohjolan Liikenne is able to measure driver's driving index and thereby develop better driving performances. In addition, the company can get an insight into drivers' driving period, breaks, and working hours. In addition, the solution saves data from certain periods and uses data to analyze it according to critical aspects that are relevant for the company. Data can be analyzed for instance with weather.

The other remarkable feature is that Telia's solution monitors the coach vehicles' condition real time. The solution is integrated to the CAN bus which all the coaches include and from there data is collected real time and the output in a readable way. No extra sensors are needed to be installed. The information that already exists can be now used to resolve problems. By adding weather information or how people move, solution can bring data bases together and analyze big data.

4.3 Case III: Delete

Delete Finland Oy (later Delete) is one of the leading providers of full-service environmental services in the Nordic countries. The company was established in 2010. Delete provides business-critical services that require specialized expertise and specialized equipment in three business areas: cleaning services, demolition services, and recycling services.

Delete's priority is to optimize maintenance processes and furthermore to improve their customers' business. Unpredictable demand of maintenance or drainage are usually unpleasant and rarely expensive for customers. Customers' daily actions are being paused during the time needed to manage these kinds of sudden drainages. Delete tested Narrow Band IoT (NB-IoT) solution as a pilot in order to obtain how NB-IoT will help to anticipate maintenance. Delete wants to experiment with technology on how to avoid unexpected service disruption in restaurants and car wash lines and enable proactive maintenance and planning. Today, Delete drains hundreds of wells monthly and most of them at short notice. With the experiment, they aim to create new stable processes that decrease unnecessary visits, develop processes according to better planning, save in costs, and, due to all these, enhance customers' daily business. "The wastewater from restaurants and service stations carries sediment that accumulates in sewer wells built for this purpose. The sensors installed in the wells allow us to monitor the amount of grease and sand accumulated in the wells in real time, while also anticipating the need for emptying the," says Markku Salminen, Director of Development and HSEQ.

Telia generates the pilot with a NB-IoT communications network, cloud data solution and a service interface. For the first time in Finland, NB-IoT remotely read sensors that are used to determine the drainage needs of a restaurant's grease separator wells and a service station's car wash line. NB-IoT technology can be used to track up to thousands of IoT devices. In the pilot, NB-IoT sensors are being installed to anticipate the maintenance and drainage needs of the sand separator wells at Stockmann's restaurant in Helsinki and the Neste K Hatanpää and Neste K Kekkosentie car wash line in Tampere. Pilot's NB-IoT takes advantage of existing 4G networks, but is also compatible with future 5G networks.

Narrowband IoT (NB-IoT) is a global standardized network technology that leverages existing 4G and 5G networks. With NB-IoT, one can connect many devices to network cheaply and reliably. The data sent by the devices can be used to monitor real-time operational and production processes. The battery of the NB-IoT sensor that collects and transmits data can last up to 10 years. It is activated and transmits data only when the programmed measurement limit is exceeded. Hundreds of thousands of devices can be connected to a single access point.

5. Cross-case conclusions

When an enterprise acquires an IIoT solution as a part of the business operations, a change in the organization is always required. The change has a direct impact on the operational process, resource planning, and people that are operating within the solution in the context. The change also affects employees who are working to provide the service. Every IIoT project with its implementation and accustoming phase in the organization requires time in which the enterprise should be prepared. In order to succeed, the change always requires identifying the change objects early enough and defining the relevant process points. However, the essential prerequisite for the success is the commitment of the uppermost management.

In one analyzed case, the enterprise outlines its new operating process by completely redesigning it based on digitalization and data. In another case, the enterprise adapts new operating processes to apply its own operating environment. Using data to streamline business processes does not bring all the potential benefits to the enterprise. The case study result reveals that when the project as a whole is successful, it will provide the company with benefits in terms of productivity, efficiency, and competitiveness. The change project itself includes, among other things, a clear definition of the cause and goals of the change, communication, staff engagement, and evaluation.

The data provided by IIoT are a valuable asset compared to the competitors of the case enterprises. By analyzing data properly and applying it to the enterprise's own business environment and processes, one is possible to gain business benefits in financial as well as international market aspects.

The study cases showed that enterprises that have strong support and contribution from management team are able to implement IIoT solution within the enterprise. The management team or the CEO of the company drives change projects other than this and they are open-minded of new technical possibilities in their industry. They believe that if they do not take advantage of technical innovation solutions, someone else in the same industry will.

In addition, the individual case studies showed that motivation for each organization level is essential in order to succeed in the implementation of the change project. The new IIoT solution needs to serve motivation for each department: CEO, financial, resource planning, logistics, service and driver's perspective.

In the future, AI will be a fundamental part of business in most sectors. The data-driven digital transformation creates new and modifies existing business processes, culture, and customer experiences to meet changing business and market requirements. Today, the lack of good-quality data in enterprises is the biggest barrier for fully exploiting AI. With good planning, new IIoT solutions can bring good-quality data, but they should be integrated into existing systems not always containing good-quality data. When the amount of good-quality data grows, possibilities to exploit AI improve. However, the success factor of data-driven digital transformation depends on the business strategy and the commitment of the top management, who should put the business strategy into practice.

Author details

Jyri Rajamäki[1*] and Petra Tuppela[2]

1 Laurea University of Applied Sciences, Espoo, Finland

2 Division X – Telia Company, Helsinki, Finland

*Address all correspondence to: jyri.rajamaki@laurea.fi

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Chapter

Big Data Analytics and Its Applications in Supply Chain Management

Saeid Sadeghi Darvazeh, Iman Raeesi Vanani and Farzaneh Mansouri Musolu

Abstract

In today's competitive marketplace, development of information technology, rising customer expectations, economic globalization, and the other modern competitive priorities have forced organizations to change. Therefore, competition among enterprises is replaced by competition among enterprises and their supply chains. In current competitive environment, supply chain professionals are struggling in handling the huge data in order to reach integrated, efficient, effective, and agile supply chain. Hence, explosive growth in volume and different types of data throughout the supply chain has created the need to develop technologies that can intelligently and rapidly analyze large volume of data. Big data analytics capability (BDA) is one of the best techniques, which can help organizations to overcome their problem. BDA provides a tool for extracting valuable patterns and information in large volume of data. So, the main purpose of this book chapter is to explore the application of BDA in supply chain management (SCM).

Keywords: big data, analytics, supply chain analytics, manufacturing, finance, healthcare, demand planning, procurement management, customized production, inventory management

1. Introduction

Big data are characterized as the gigantic or complex sets of data, which usually encompass extend of more than exabyte. It outstrips the traditional systems with limited capability in storing, handling, overseeing, deciphering, and visualizing [1]. Nowadays, data are expanding exponentially and are anticipated to reach zettabyte per year [2]. The scholarly world and professionals concur that this surge of data makes modern opportunities; subsequently, numerous organization attempted to create and upgrade its big data analytics capabilities (BDA) to reveal and gain a higher and deeper understanding from their big data values. The study of big data is persistently advanced and extended, and the most properties of big data are presently extended into "5 V" concept containing variety, verification/veracity, velocity, volume, and value [3, 4]. Akter et al. recommended BDA as one of the most important factors affecting organizational performance [5]. By progressing BDA, organizations could make better understanding from their customer's needs, provide suitable service to satisfy their needs, improve sales and income, and penetrate into new markets. Several research studies indicated the big data applications in various sectors such as financial services sector, marketing, bank industry, insurance industry, logistics, and manufacturing [6]. However, the present book chapter indicates the benefits of big data application in extracting new insights and creating new forms of value in ways that have influenced supply chain relationships. Regarding this purpose, first, the authors defined the key concepts of BDA and its role in predicting the future. Second, the authors paid to the role of statistical analysis, simulation, and optimization in supply chain analytics. Third, the authors had a review on application of BDA in supply chain management areas. Forth, the authors provided a brief information about application of BDA in different types of supply chain. Fifth, the authors presented some insight into future application of BDA in supply chain, and lastly, the book chapter ends with the conclusion, some managerial implications, and recommendations for future research.

2. BDA capabilities

To fully understand the impact and application of BDA, we first need to have a clear understanding of what it actually is. As a simple definition, big data refer to large quantity of data. Big data specifically refer to large data sets whose size is so large that the quantity can no longer fit into the memory. These data can be captured, stored, communicated, aggregated, and analyzed. As the volume of data has grown, the need to revamp the tools has used for analyzing it. These data do not ought to be set in neat columns and rows as traditional data sets to be analyzed by today's technology, not at all like within the past. Big data appear completely in different kinds of data. They incorporate all types of data from every possible source. They can be structured, semi-structured, or fully unstructured. As another categorization, big data consist of numerical data, image data, voice, text, and discourse. They can come in the form of radio-frequency identification (RFID), global positioning system (GPS), point-of-sale (POS), or they can be in the frame of Twitter feeds, Instagram, Facebook, call centers, or customer blogs. Today's progressed analytical technologies empower us to extract knowledge from all kinds of data. Analytics is a mix of math and statistics to large quantities of data. BDA mean using statistics and math in order to analyze big data. Big data without analytics are just lots of data. The authors have been accumulating a lot of data for years. Analytics without big data is simply mathematical and statistical tools and applications. Companies can extract intelligence out of these huge amounts of data. This is made possible through today's massive computing power available at a lower cost than ever before. However, combining the big data and analytics makes the different tools that help decision makers to get valuable meaningful insights and turn information into business intelligence.

3. Supply chain analytics

The supply chain is the number of firms from raw material suppliers to producer/central organization, wholesalers, retailers, customers, and end users. The supply chain not only includes physical flows involving the transfer of materials and products but also consists of information and financial flows. Supply chain analytics (SCA) means using BDA techniques in order to extracting hidden valuable knowledge from supply chain [7]. This analytics can be categorized into descriptive, predictive, and prescriptive analytics [7, 8]. Well-planned and implemented decisions contribute directly to the bottom line by lowering sourcing, transportation, storage, stock out, and disposal costs. Hence, using BDA techniques in order

Category	Features
Descriptive Analytics What happened and	• Foundational • Filters big data into useful nuggets and interpretable information • Provides a historical summary of what happened in the past • Focus on minimizing bias Example: providing historical insights regarding the company's production, financials, operations, sales, finance, inventory, and customers.
Predictive Analytics What might happen?	• Insightful • What-if analysis • Forecasting supply chain requirements • Focus on minimizing the combined bias and variance Example: Analyzing past trends to estimate future needs, supply and demand, set accurate delivery time and etc.
Prescriptive Analytics What should we do?	• Strategic • Scenario and knowledge based • Optimization and automation of decisions Example: optimizing production, scheduling and inventory.

Table 1.
Features of descriptive, predictive and prescriptive analytics.

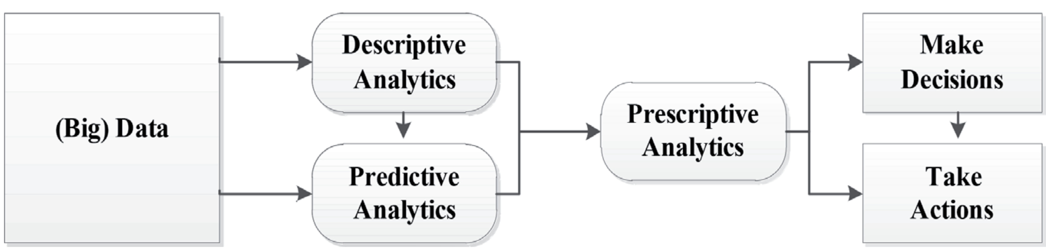

Figure 1.
Using descriptive, predictive and prescriptive analytics to make decisions and take actions.

to solve supply chain management problems has a positive and significant effect on supply chain performance. For a long time, managers and researchers have used statistical and operational research techniques in order to solving supply and demand balancing problems [8, 9]. However, recent progress in the use of analytics has opened new horizons for managers and researchers. The summary of the challenges and features of the three types of analytics is shown in **Table 1**. Also, the relationships among descriptive, predictive, and prescriptive analytics to make decisions or take actions are shown in **Figure 1**.

The different potential advantages that can be achieved utilizing data-supported decision making have incited academicians and researchers to pay attention to the possible integration of big data in SCM. This has resulted in the number of scholarly articles on this topic, which has risen precipitously in recent years. The importance of using BDA techniques in SCM is true to an extent that organizations will not stand a chance of success in today's competitive markets. Since 2010, numerous articles have been published, which emphasized on the application of BDA in SCM and their major achievements [2, 3, 10–13]. Since 2011 to 2015, Mishra et al. identify the influential and prominent researchers and articles with most citations carried out a bibliographic analysis of big data. The results indicated that the number of articles in the field of BDA has increased [14]. Barbosa et al. conducted a systematic literature review to investigate the application of BDA in SCM areas. The results indicated that BDA techniques usually use the predictive and prescriptive approaches rather than descriptive approach [10]. Dubey et al. carried out a research in order to identify the effects of big data and predictive analysis on two aspects of sustainability, including environmental and social aspects. Data were collected from 205 manufacturing companies, and using structural equation modeling based on partial least square was analyzed. The results indicated that big data have a positive and significant effect on social and environmental components of sustainability [15]. Gupta et al. carried out a systematic literature review based on 28 journal articles to investigate the impact of using BDA techniques on humanitarian SCM [16]. Gupta et al. investigated the applications of big data in the context of humanitarian SCM based on 28 journal articles. They proposed some important future research directions based on key organization theories such as complexity theory, transaction cost economics, resource dependence theory, resource-based view, social network theory, institutional theory stakeholder theory, and ecological modernization theory. Zhao et al. proposed a multiobjective optimization model for green SCM using BDA approach. They considered three different scenarios for optimizing the inherent risk associated with hazardous materials, carbon emission, and overall costs. They utilized a big data approach to acquire data and manage their quality [17]. Song et al. studied the problems and challenges arising due to big data in the context of environmental performance evaluation along with summarizing latest developments in environmental management based on big data technologies [18].

- In descriptive analysis, the following questions are answered:

What has happened, What is happening, and Why, In this process, visualization tools and online analytical processing (OLAP) system are used and supported by reporting technology (e.g. RFID, GPS, and transaction bar-code) and real-time information to identify new opportunities and problems. Descriptive statistics are used to collect, describe, and analyze the raw data of past events. It analyzes and describes the past events and makes it something that is interpretable and understandable by humans. Descriptive analytics enables organizations to learn from their past and understand the relationship between variables and how it can influence future outcomes. For example, it can be used to illustrate average money, stock in inventory, and annual sale changes. Descriptive analytics is also useful to an organization's financials, sales, operations, and production reports.

- Predictive analytics techniques are used to answer the question of what will happen in the future or likely to happen, by examining past data trends using statistical, programming and simulation techniques. These techniques seek to discover the causes of events and phenomena as well as to predict the future accurately or to fill in the data or information that already does not exist. Statistical techniques cannot be used to predict the future with 100% accuracy. Predictive analytics is used to predict purchasing patterns, customer behavior and purchase patterns to identifying and predicting the future trend of sales activities. These techniques are also used to predict customer demands, inventory records and operations.

- Prescriptive analytics deals with the question of what should be happening and how to influence it. Prescriptive analytics guides alternative decision based on predictive and descriptive analytics using descriptive and predictive analytics, simulation, mathematical optimization, or multicriteria decision-making techniques. The application of prescriptive analytics is relatively complex in practice, and most companies are still unable to apply it in their daily activities of business. Correct application of prescriptive analytics techniques can lead to optimal and efficient decision making. A number of large companies have used data analytics to optimize production and inventory. Some of the crucial scenarios that prescriptive analytics allows companies to answer include in the following:

a. What kind of an offer should make to each end-user?

b. What should be the shipment strategy for each retail location?

c. Which product should launch and when?

Statistical analysis, simulation, optimization, and techniques are used to supply chain decision making [19].

3.1 Statistical analysis

Statistical analysis basically consists of two types of analysis: descriptive and inferential. In descriptive statistics, past data are used to describe or summarize the feature of a phenomenon; it uses either graphs or tables or numerical calculations. Inferential statistics are used to deduce the properties of phenomena and predict their behavior based on a sample of past data. **Table 2** shows differences between descriptive and inferential analyses. Both quantitative and qualitative methods can be used simultaneously to take the advantage of both the methods and the right decisions. Statistical analysis is used when faced with uncertainty, such as in distribution, inventory, and risk analysis. Statistical multivariate techniques are also used for supply chain monitoring to effectively manage the flow of materials and minimize the risk of unintended situation [20]. Given the volume, variety, veracity, and velocity of big data, the supply chain needs robust and easy techniques for analysis. Traditional statistical methods are no longer responsive because the massive data lead to noise accumulation, heterogeneity, and so on. Therefore, proposing and applying effective statistical methods are very important, and major attention has been paid to this issue recently. For example, in a research, a parallel statistical algorithm is presented to do a sophisticated statistical analysis of big data. This algorithm uses specific methods such as Mann-Whitney *U* testing, conjugate gradient, and ordinary least squares to model and compare the densities and big data distribution squares [2].

3.2 Simulation

Manufacturers need simulation tools to optimize the product development process and increase the creativity, speed the time-to-market product, reduce the production costs, and create the innovation. Simulation provides many proven benefits for

Basis for comparison	Descriptive statistics	Inferential statistics
What it does?	Organizing, analyzing, and presenting data in meaningful way	Comparing, testing, and predicting data
Form of final result	Charts, Graphs, and Tables	Probability
Usage	To describe the current situation	To explain the chances of occurrence of an event
Function	It explains the data that are already known to summarize	It attempts to reach the conclusion to learn about the population that extends beyond the data availability

Table 2.
Comparing descriptive and inferential analyses.

each stage of the product design and manufacturing process, for example, producing more innovative products with greater efficiency for the customer and creating a better experience for them [21]. For example, when consumer goods giant Proctor & Gamble develops new dishwashing liquids, they use predictive analytics and modeling to predict how moisture will excite certain fragrance molecules, so that the right scents are released at the right time during the dishwashing process. Modeling and simulation techniques should be used to develop the application of large data, for example, simulation-driven product design. In today's competitive environment, the use of simulators to produce innovative products is considered a challenge. Because manufacturers have to continually drive their operational efficiencies, meet the cost, require the time-to-market product, and predict the customer preferences.

Modeling and simulation help developer to run the "what-if" analysis under different system configuration and complexity [22]. Shao et al. developed a simulation model to analyze the huge data collected from the surrounding and shop floor environment of a smart manufacturing system. This model improved the decision making in this production system [23]. For example, as a predictive tool, simulation can help the manufacturers to predict the need for machines and additional equipment based on customer order forecast and learning from other historical data such as cycle time, throughput, and delivery performance. LLamasoft [24] outlined some examples of where supply chain simulation can be used as follows: predicting the service, testing the inventory policy, analyzing the production capacity, determining the asset utilization, and validating the optimization result. SCA provides new methods for the simulation problem with a large amount of data. Nowadays, there are several simulation software that allow to evaluate the performance of a system before its creation. Enterprise dynamics (ED) is one of the strongest and most used software that researchers and practitioners use it to simulate SCM issues.

3.3 Optimization

The optimization technique is a powerful tool for supply chain data analytics [25]. Optimization techniques by extracting the insights and knowledge of the enormous data generated by complex systems that include multiple factors and constraints such as capacity and route can analyze multiple objectives such as demand fulfillment and cost reduction. Finally, using supply chain optimization techniques along with multiuser collaboration, performance tracker, and scenario management enables organizations to achieve their different goals. The use of optimization techniques supports supply chain planning and also increases the accuracy of planning but presents the large-scale optimization challenge [7]. Slavakis et al. [26] have used several signal processing and statistical learning techniques to analytic optimization, principal component analysis, dictionary learning, compressive sampling, and subspace clustering. Based on SCOR supply chain model, Souza explored the opportunities for applying BDA in SCM [8]. BDA play a critical role at all operational, tactical, and strategic levels of the supply chain; for example, in the strategic level, SCA is used for product design, network design, and sourcing; in the tactical and operational levels, SCA can also be used for procurement, demand planning, logistics, and inventory.

4. Application of BDA in SCM areas

In the production department, a large amount of data is generated by external channels and also by internal networks that contain sensor networks or instrumentation on the production floor. Using big data to tighter analysis and integration of these databases, it can improve the efficiency of the distribution and sales process and the continuous monitoring of process and devices. Manufacturing companies need to use big data and analytics techniques to grow their manufacturing sector. Predictive maintenance of equipment is an immediate segment in this sector ripe for growth. Due to the large number of vendors, as well as the variety of their evaluation and selection indicators, the process of selecting the right and optimal vendor for the supply chain is difficult. Applying Cloud Technologies to selecting vendors is making a big impact. With new systems, access and exposure to data are more intuitive and customer focused with the power of APIs and integration to modern big data applications and analytic packages. A review in the literature indicates that BDA can be used in several areas of SCM. In the following sections, an overview of BDA applications in different areas of supply chain is provided [27].

4.1 BDA and supplier relationship management

Supplier relationship management involves establishing discipline in strategic planning and managing all interactions with organizations' suppliers in order to reduce the risk of failure and maximize the value of these interactions. Establishing close relationships with key suppliers and enhancing collaboration with them are an important factor in discovering and creating new value and reducing the risk of failure in SRM. Strategic resources and supplier relationship management (SRM) are the success factors of organizations, which focus on relationship management and collaboration. Using BDA techniques can provide accurate information on organizational spending patterns that help manage supplier relationships [28]. For example, big data can provide accurate information on the return on investment (ROI) of any investment and in-depth analysis of potential supplier. In a study, fuzzy synthetic evaluation and analytical hierarchy process (AHP) were used to supplier evaluation and selection, given the high capacity of big data processing as one of the evaluated factors has been used [29]. The objective is to select supply partner that can adapt to the future challenges from big data.

4.2 BDA and supply chain network design

Supply chain design is a strategic decision, which includes all decisions regarding the selection of partners of the supply chain and defines company policies and programs to achieve long-term strategic targets. Supply chain network design project involves determining supply chain physical configuration that affects most business units or functional areas within a company. In designing the supply chain network, it is important to determine the customer satisfaction and supply chain efficiency. The purpose of supply chain design is to design a network of members that can meet the long-term strategic targets of the company. When designing a supply chain, the following steps must be followed: (1) define the long-term strategic targets; (2) define the project scope; (3) determine the form of analyses to be done; (4) the tools that will be used must be determined; and (5) finally, project completion, the best design.

Selecting the optimal supply chain design and appropriate planning, the company will achieve a significant competitive advantage. Wang et al. (2016b) proposed a mixed-integer nonlinear model for locating the distribution centers, utilized big data in this model, and randomly generated big datasets applied for warehouse operation, customer demand, and transportation. They assumed that the behavioral dataset has been analyzed using marketing intelligence tools. Their findings show that big data could provide all the necessary information about penalty cost data and service level; therefore, it is a very powerful tool for complex distribution network design [30]. A study investigates the application of BDA in design intervention such as healthcare, disaster relief, and education in supply chain [31]. Since humanitarian data have the characteristics of high volume, high diversity, accuracy, and speed, BDA can be used in the humanitarian supply chain.

4.3 BDA and product design and development

One of the major concerns of adaptable product manufacturers is ensuring that these products conform to their customers' preferences. As customers' preferences and expectations change throughout the product lifetime, designers need tools to predict and measure those preferences and expectations. Lack of enough information about customers' preferences and expectations is an important issue in the product design process. If designers continuously monitor customer behavior and access up-to-date information on customer preferences, they can design products that meet customer preferences and expectations. Continuous monitoring of customer behavior, product design, and manufacturing process generated huge data that are considered as big data. Collecting, managing such huge data, and applying new analytical methods to gain insights and useful information and then apply them to decisions can reduce uncertainty [32]. Engineering design is defined as a process of transforming customer needs into design specifications [33]. Data science (DS) is defined as a process of transforming observed world reality data into comprehensible information for decision making [34]. Although different approaches are available for product design [35, 36], all of these methods are common in DS perspective. A schematic view of the design process is shown in **Figure 2**.

Big data are going to impact many industries, and product design is no exception. That is in part because engineers will increasingly design sensors and communication technology into their products. Therefore, in the process of supply chain design, the product specificities of the company must be considered, and all partners and constraints of the supply chain must be integrated at the design stage [37]. Supply chain design according to product design creates competitive advantage and flexibility in the supply chain [38]. Recently, BDA techniques have been used for product design and development, which lead to the production of new products according to customer preferences. Applying BDA to product design enables the designer to be constantly aware of customer preferences and expectations that lead to produce a product according to their needs and preferences [32]. Designers can use online behavior and customer purchase record data to predict and understand the customer needs [39]. Designers can identify product features and predict future product trends by continually monitoring the customer behavior and informing the customers' opinions and needs. In the automotive industry, the importance of big data is derived from the vehicle that shows huge performance data and customer needs [40]. The ultimate goal of companies producing consumer durables is to maintain their competitiveness over the longest possible period [41]. Nowadays, this is facilitated the implementation

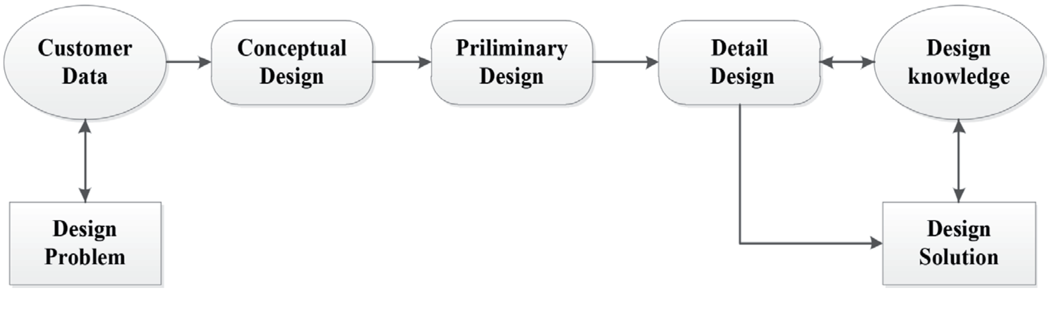

Figure 2.
Design process from data science view [32].

of the concept of (run-time) data-driven design. The recent developments of data analytics and application of data analytics tools have opened up a new path for generating knowledge for product enhancement and achieving their objectives [42]. As one doctrine, product developers can achieve a perpetual enhancement of their products and services based on real-life use, work, and failure data. Though numerous data analytic (software) tools and packages have been developed for extracting product-associated data, exploiting data analytic methods and tools in product enhancement is still in a rather premature stage [43]. Designers still face many challenges and should consider many limitations. Reportedly, choosing the most relevant data analytic tools (DATs) and using them in design projects are not trivial for designers [44].

Here are some other ways the design engineering might change as a result of big data it enables:

- Better-informed product development: How would the way organizations design product's change if they could learn not only how customers are using them, but also where they are having trouble with them and what features they are ignoring altogether? That information is going to be available to organizations soon. Mechanical engineers have the opportunity for product insights that were never possible before. With an Internet of Things (IoT)-enabled device, products can stream usage data back to engineers. Imagine, for example, a bike fork that captures force measurements or a utility cabinet that transmits internal temperature readings.

- More empowered engineering: Traditionally, engineers rely on marketers, customer visits, or their own best guesses to design the competitive products. However, big data could provide volumes of reliable feedback that none of those channels offer. Products are generating a lot of information during their lifecycle, and new trends for Internet of Things will bring even more information to manufacturing companies. A tremendous amount of data will be collected from connected devices, and this can be transformed into consumable information assets. Because products will be able to talk back to engineers, engineers will be empowered like never before to have a direct impact on the competitiveness of their products.

- Faster product development: As much more data reside on the cloud, more people can securely reach information faster (and at a lower cost) compared to working within corporate networks and specific platforms. That may lead to more participants and disciplines involved in the product development cycle early on. The IT infrastructure of cloud computing will enable new approaches for concurrent CAD design and system engineering principles combining mechanical, electrical, and software in product development.

Concluding with all these different disciplines in product design connected and accessing the big data throughout the various phases of the design cycle, the engineers will be confronted with many surprises and few unpleasant shocks as well. The real challenge will lie in solving these minute hassles and in developing better products reaching a new level in the product design as a whole.

4.4 BDA and demand planning

Many supply chain executives are keen to improve demand forecasting and production planning with big data [45]. Accurate demand forecast has always been a major puzzle in SCM [46]. Trace consumer loyalty, demand signal, and optimal price data can be determined by BDA. However, one of the challenges the organizations face is the ability to apply advanced hardware and software and algorithm architecture [47]. BDA allow to identify new market trends and determine root causes of issues, failures, and defects. Data analytics can predict customers' preferences and needs by examining customer behavior, which can drive creativity and innovation in business services [48]. In one study, a model was presented to predict the electric vehicle charging demand that used weather data and historical real-world traffic data. This model enables operators to plan the generation profiles and operation by determining the charging demand [49]. Another study presents a model for predicting demand for air passenger demand, which uses big data to estimate air passenger demand. The results of this study show a 5.3% prediction error [50].

4.5 BDA and procurement management

As tactical and operational decisions, procurement consists of a series of action mechanism and contracting [8]. Logistic organizations, given the high volume of widely dispersed data generated across different operations, systems, and geographic regions, need advanced systems to manage these enormous data, as well as skilled professionals who can analyze these data, and extract valuable insights and knowledge into them in order to apply them in their planning and decisions. In the past, organizations faced laborious processes that took several weeks to gather internal and structural data from the operations and transactions of the company and its partners. But today, at a significant speed, in real time, in many cases, all of the diverse structural, nonstructural, internal, and external data generated from automated processes are made available to these organizations. SCA can be used to manage suppliers' performance and supply chain risk [7]. In one study, external and internal big data have been used to quickly identify and manage the supply chain risk [51]. For example, informing the social media and news about exchange rate movement and disasters affects the supply chain. Applying this framework to identify supply chain risk enables real-time risk management monitoring, decision support, and emergency planning. Schlegel [52] also provided a big data predictive analytic framework to identify, evaluate, mitigate, and manage the supply chain risk.

4.6 BDA and customized production

With BDA, manufacturers can discover new information and identify patterns that enable them to improve processes, increase supply chain efficiency, and identify variables that affect production.

In today's global and interconnected environment, the supply chains and manufacturing processes involve long and complex processes; it should be possible to examine all components of each process and link supply chain in granular detail to simplify the processes and optimize the supply chain. Data analytics enables manufacturers to accurately determine each person's activities and tasks through timely and accurate data analysis of each part of the production process and examine entire supply chain in detail. This ability enables manufacturers to identify bottlenecks and reveal poorly performing processes and components. In the past, centralized production and production at scale were not rational because they focused only on the ordering of a small group of customers, while today's BDA have made it possible to accurately predict customer demands and tastes for customized products. Some studies have investigated the applied techniques of BDA in the production area. For example, Zhong et al. applied RFID-enabled big data to support shop floor logistic planning and scheduling [53]. He then implemented the Physical Internet concept by using the Internet of Things, wireless technology, and BDA to create an RFID-enabled intelligent shop floor environment [54]. Stich et al. have used BDA techniques to predict demand and production levels in manufacturing companies [55]. On the other hand, early additive manufacturing (also called 3D printing) was developed in the 1980s. This new technologies and trends are emerging that will change the rules of supply chain design and management [56]. 3D printing is any of various processes in which material is joined or solidified under computer control to create a three-dimensional object [57]. 3D printing is an innovative technology that makes possible to create a physical object from a digital model. Understanding the uses and implications of big data and predictive analytics will be urgent as additive manufacturing makes traditional models of production, distribution, and demand obsolete in some product areas [58].

4.7 BDA and inventory management

Inventory control is the system that involves requisition process, inventory management, purchase, and physical inventory reconciliation. The following key objectives define the design of inventory control:

- informing the quantity of goods in warehouse and also the amount of goods needed in the warehouse;
- facilitating the requisition process to finish in time;
- automatic recording and backorder serving;
- minimizing the inventory by analyzing previous purchasing and consumption patterns of the organization;
- using the automated tools to facilitate management of the inventory, servicing, and purchasing; and
- improving the financial control of the inventory through a timely and regular checkup of the inventory balances with the physical counts.

Big data by integrating business systems in distribution of nonperishable products improve operational efficiency on a broad scale while also delivering greater profitability. The benefits of using BDA in supply chains are listed below. Below are some ways the big data are changing the way companies manage inventory. Following are a few examples of ways big data manage inventory.

Improved operational efficiency: Due to the possibility of continuous monitoring and analysis of operational data by operational managers and better access to metrics, efficiency has improved, and bottlenecks have been removed. Big data increase efficiency and performance in whole supply chain.

Maximized sales and profits: Using the real-time data, financial managers can continuously monitor and analyze these data and manage the profit margins with greater insights to ensure maximum profitability from their investment.

Increased customer service satisfaction: The access to real-time data and the ability to timely analyze these data provide operational managers with the ability to match their inventory levels with customer orders and tastes, which will increase customer satisfaction. Data analysis techniques can also be used to predict spikes or depressions in customer demand and seasonal trends to accurately inventory planning at different times.

Reduced costs by migrating to the cloud: A Software-as-a-Service (SaaS) approach to IT management means that the cloud-based nature of big data reduces hardware and maintenance costs. It can also be seamlessly integrated to existing systems with a minimum of expense.

There are only two publications in the field of BDA applications in the inventory management in Perish or Publish Software. Big data create significant competitive advantage by connecting and integrating internal production system with external partners (customers and suppliers) in inventory management [59]. With the help of big data, an automated inventory control system can be designed [60]. Data analysis techniques can be used to analyze the data, extract the relationships between them, and predict the optimal rate of inventory ordering [7].

4.8 BDA and logistics

The logistic industry has undergone a fundamental transformation due to the emergence of large volumes of data and devices, emission concerns, complex regulatory laws, changing industry models, talent limitations, infrastructure, and rise of new technology. In this industry, the standardization of structure and the content of data interchanges must be given great importance to improve and facilitate communication and collaboration between different sectors, including shippers, manufacturers, logistic companies, distributors, and retailers, as well as to the creation of new common business processes. However, reducing costs by driving down excessive inventory, both staged and in-transit, proactively responding to inbound and outbound events and sharing assets has become critical in today's supply chain environment.

Today, due to the high volume of data generated from various sources such as sensors, scanners, GPS, and RFID tags, as well as due to integrating business judgment and fusing multiple data sources, powerful techniques are needed to quickly and timely analyze these data and provide real-time insights for a timely and accurate decision making. Given the high volume of orders and massive flow, huge data sets and methods for timely analysis are needed to manage and maintain them. Since high volumes of data such as size, weight, origin, and destination are being generated daily for millions of shipments, there is a huge potential for new business creation and operational efficiency and customer experience improvement. Organizations need data platforms and data analytic processes to pervade their insights into organizations, which are not easy, and it is a new challenge for organizations. Infosys offerings are designed to help logistic companies rethink, evolve, and achieve their vision through a three-pronged strategy:

- Boundary-less information: A strategic alliance has been created among customers, logistics enterprises, and suppliers in the logistic industry, and the huge data set produced by the industry is placed on logistic technologies such as Warehouse Management Solutions (WMS), Transport Management System (TMS), supply chain execution systems, and IOT devices to share and access all members. A platform in the supply chain manages and integrates a huge variety of data created from different internal and external systems and provides the right validations and governance to improve the trustworthiness of the data and make right data available to business users in a self-service manner for exploratory analysis and insight generation.

- Pervasive analytics: An open and adaptive framework is needed to integrate seamlessly the different insights into an organization and to apply them effectively.

- Progressive organization: The dynamic changes in markets and the emergence of advanced data management and analysis technologies as well as "boundary-less" paradigm make organizations to abandon traditional BI analytic methods and governance structures and use new advanced techniques. Organizations will become knowledge-based organizations that utilize powerful horizontal platform and supportive tools that are in line with associated security, next-gen data sets, and business semantic policies.

Many research studies pointed to the application of BDA in the areas of transportation, and logistics. BDA have been used to gain competitive advantage and provide new services in logistics [61]. Maritime companies have also used prescriptive and predictive BDA to solve their planning problems [62]. In another study, we have used big data to share transportation capacity in order to improve the efficiency of urban healthcare services [63]. It is an obvious fact that BDA can support all supply chain activities and processes and create a supply chain strategies/agiler logistics.

4.9 BDA and agile supply chain

The most successful organizations create supply chains that can respond to unexpected changes in the market [64]. Choi et al. argue that big data have significant effects on operation management practices [65]. Gunasekaran et al. further argue that supply chain disruptions have negative effects, and agile supply chain enablers were progressively used with the aid of big data and business analytics to achieve better competitive results [66, 67]. Srinivasan and Swink further argue that although BDA have been using to understand customer intentions/behaviors, the use of analytics for supply chain operational decisions is less understood [68]. Gunasekaran et al. [66] and [67] argue that big data and predictive analytics have positive effects on supply chain performance and organizational performance [67, 68]. Swafford et al. found that IT capability has positive effect on SCA [69]. Srinivasan and Swink noted that supply chain visibility is a prerequisite for building data analytic capability and vice versa [68]. Supply chain visibility and BDA are complementary in the sense that each supports the other [66, 67]. Supply chain visibility is a desired organizational capability to mitigate risk resulting from supply chain disruptions [70]. Following Srinivasan and Swink's arguments that organizations investing in building supply chain visibility capability are likely to invest in BDA [68], Dubey et al. found a positive impact of supply chain visibility on SCA [15]. By accurately anticipating consumer trends based on historical data, real-time data, and future predictions, organizations can put that knowledge to work to become more agile, efficient, and responsive.

Some other studies have been done to examine BDA that support the advanced supply chain agility [71]. Many parts and processes of the supply chain BDA have been widely used; however, publications regarding data analysis applications in the supply chain remain limited. Many parts and processes of the supply chain BDA have been widely used; however, publications regarding data analysis applications in strategic sourcing and inventory management are still limited. People working in this area should be able to extract knowledge and insight into the enormous data available and use it in their planning and decisions, and this is a challenge for them. Big chain analytics will help optimize decision making by aligning organization's strategy to the sourcing strategies and providing proper insights [7]. BDA also improve inventory decision through a better understanding of uncertain customer demand [72].

4.10 BDA and sustainable supply chain

Although sustainable SCM has been discussed in corporate offices for some time, actually implementing the sustainability phenomenon in the extended supply chain has proved difficult [73]. Nevertheless, large corporations perceive sustainability efforts as long-term investments aimed toward building strategic resources [74]. Corporations are increasingly interested in using BDA in their sustainable efforts, which in turn give them a strategic edge [75]. According to a Mckinsey survey report, companies using BDA are able to predict the 65% of customers that make repeated purchases through shop alerts and 75% of those customers reported that they are likely to use the service again [76].

Several scholars acknowledge sustainability (environmental, social, and financial) as an emerging area for BDA applications in business [77, 78]. Therefore, BDA techniques should be applied throughout the supply chain in order to achieve full benefits [79]. As decision making in organizations has been based on data, organizations must change their strategic capabilities, which affect sustainability. Given the growing importance of sustainability and BDA, organizations must integrate these two areas to achieve sustainable competitive advantage [78, 80]. Despite the pressing need to integrate data analysis with sustainability and supply chain measures, little progress has been made so far [81]. Few scholars have addressed this issue that to achieve strategic and competitive advantages, BDA and sustainability must be integrated [78, 80]. Today's organizations must use methods to analyze high volumes of data to gain insights and knowledge in order to achieve the three dimensions of environmental, social, and economic sustainability [82].

Some studies have used big data analysis to predict natural disasters to take preventive action against them, and simulation has been used reduce the effects of these environmental hazards [83]. Big data are also collected for melting glaciers, deforestation, and extreme weather through satellite images, weather radar, and terrestrial monitoring devices. Such data are used to comprehensively study global climate change and assign specific causality [21]. Big data have also been used for community health and welfare. For example, BDA have been used in Europe and USA to identifying and predicting prostate cancer biomarkers to take preventive measures at the right time [84, 85]. Another study applied policy-driven big data to support and improve sustainability measures in various operations. For instance, to protect the environment and take the sustainable measures, computer platforms are used to collect and share environmental data (i.e., big data), and such data have used for government-led publication of data on medical records for risk mitigation and research, among the other applications [86]. However, literature on the application of BDA for supply chain sustainability has been much less explored. Thus, scholars acknowledge the need for further exploration in this domain [75, 77, 87, 88]. Furthermore, for the supply chain to be sustainable, the potential risks disrupting operations must be identified and predicted. In the next section, the authors explore the literature related to supply chain risk management.

5. Application of BDA in different types of supply chain

In the current years, BDA practices have been extensively reported. One of the main reasons is to make full usage of the data to improve productivity, by providing "the valuable right information, for the right user, at the right time." In this section, an overview of BDA applications in different companies including manufacturing, finance, and healthcare is provided.

5.1 Application of BDA in manufacturing

Despite the importance of big data in today's world, many organizations overlook the importance of using big data for their organizational performance. Proper application of BDA techniques can be used to track, analyze, and also share employee performance metrics. BDA techniques also are used to identify employees with poor or excellent performance, as well as struggling or unhappy employees. These techniques allow organizations to monitor and analyze continuously real-time data, rather than just annual investigations based on human memory. In today's world, the manufacturing industry must use advanced data analytic technologies to gain competitive advantage and improve productivity in design, production, sales, and timely product delivery processes. Approximately, manufacturing industry stores 2 exabytes of new data in 2010 [89]. Since in production lines and factories, various electronic devices, digital machineries, and sensors are used, and a huge amount of data is generated. Therefore, BDA can be used to build intelligent shop floor logistic system in factories [54, 90]. A huge amount of data also creates from design and manufacturing engineering process in the form of CAM and CAE models, CAD, process performance data, product failure data, internet transaction, and so on. Data analysis techniques can be applied to defect tracking and product quality and to improve activities of the product manufacturing process in manufacturing [91].

Data analysis techniques can also be used to predict customer demands and tastes. Raytheon Corp manufacturing company has develop smart factories through the powerful capacity of handling huge data that collect from various sources including instruments, sensors, CAD models, Internet transactions, digital records, and simulations that enable the company in real-time control of multiple activities of the production process [92]. General electric creates innovative and efficient servicing strategies by continuous observation and analysis of huge data obtained from various sensors in manufactured products including in GE's case, jet engines, locomotives, medical imaging devices, and gas turbines [93]. Schmitz Cargobull, a German truck body and trailer maker, uses sensor data, telecommunication, and BDA to monitor cargo weight and temperatures, routes, and maintenance of its trailers to minimize their usage breakdown [94]. Toyota Motor Corporation to dramatically improve its data management capabilities launches Toyota Connected as their Big Data Business Unit. Toyota also uses vehicle big data collected from connected car platform to create new business and service such as adding security and safety service and to create mobility service, traffic information service, and feedback to design [95]. The integration of BDA into manufacturing system design should move from a descriptive to a predictive system performance model over a period of time, such as using what-if analysis, cause-effect model, and simulation [96].

5.2 Application of BDA in finance

Maintaining the sustainable competitive advantage and enhancing the efficiency are important goals of financial institutions. In order to achieve sustainable competitive advantage and stay afloat in the industry, these institutions must continually use big data and appropriate analytic techniques into their business strategy. In recent years, there has been a great deal of improvement in big data and analytic techniques, and there has been a lot of investment in them. Banks and financial service organizations using big data and analytical techniques gain valuable knowledge and insights that can be used in continuous monitoring of client behavior in real time, predict their wants and needs, and provide the exact resource and service according to customer's requests and needs. Using the findings of this real-time data analysis and evaluation result in turn, it enhances overall profitability and performance. After the 2008 global financial crisis, financial institutions need to use big data and analytic techniques to gain competitive advantage [2]. Due to the high volume of financial transactions and activities, the application of big data and analytic techniques is very necessary and important in most of the financial organizations such as asset management, insurance companies, banks, and capital market. Organizations need to be able to manage their huge data and extract the knowledge and insight contained in these data and then use them in all their business processes and decision making. Bean reported that 70% of global financial service organization thought BDA was important and 63% has applied big data in their organizations [97]. According to Technavio, costs of big data technology in the global financial industry will grow by 26% from 2015 to 2019, which suggests the importance of big data in this industry [98]. BDA techniques provide important insights through continuous monitoring of customer behaviors and data analysis, which improve customer intelligence such as customer risk analysis, customer centricity, and customer retention. BDA is applied to all transactions and activities of the financial service industry, including forecasting and creating new services and products, algorithmic trading and analytics, organizational intelligence (such as employee collaboration), and algorithmic trading and analytics. BDA is also used to support risk management and regulatory reporting activities [99]. Chief Financial Officer (CFO) should use analytic techniques to analyze data of big data and extract knowledge and insights into them and then use information and knowledge in their strategic decision making. Therefore, Chief Financial Officer (CFO) can apply a business analytics and intelligence tool to improve data accuracy, make better decisions, and provide greater value [100]. Data analysis techniques can also be used in financial markets to examine the market volatility and calculate VPIN [101]. Financial institutions can use real-time decision making and predictive modeling to gain a competitive advantage in the dynamic financial markets [102]. The Barclays Finance Company has widely used big data to support its operations and create and maintain primary competitive advantage. They apply big data in many areas such as financial crime, treasury, financial crime, risk, intelligence, and finance [103]. Deutsche Bank also has applied the big data in their businesses. Deutsche Bank has set up a Data Lab that provides internal data, analytics consultancy, test-out business idea, and technology support to other division and business function [104].

5.3 Application of BDA in healthcare

In the health industry, a large amount of data is generated to control and monitor the various processes of treatment, protection, and management of patients' medical records, regulatory requirements, and compliance. Big data in healthcare are critical due to the various types of data that have been emerging in modern biomedical including omics, electronic health records, sensor data and text, and imaging, which are complex, heterogeneous, high-dimensional, generally unstructured, and poorly annotated. Modern and strong techniques are needed to quickly manage and analyze these data. "Big data" in the healthcare industry include all data related to well-being and patient healthcare. According to the report of US Congress in August 2012, big data are defined as "large volumes of high velocity, complex, and variable data that require advanced techniques and technologies to enable the capture, storage, distribution, management, and analysis of the information." Big data in healthcare encompass such characteristics as high-dimensional, variety, heterogeneous, velocity, generally unstructured, poorly annotated, and, with respect specifically to healthcare, veracity. Big data in the healthcare industry include these characteristics of high-dimensional, variety, heterogeneous, velocity, generally unstructured, poorly annotated, and, with respect specifically to healthcare, veracity. Application of analytical techniques in Medical Healthcare System includes image detection, lesion detection, speech recognition, visual recognition, and so on. Existing analytical techniques can be applied to the vast amount of existing (but currently unanalyzed) patient-related health and medical data to reach a deeper understanding of outcomes, which then can be applied at the point of care. A large amount of diverse healthcare data from personal medical records to radiology images, laboratory instrument reading, and population data is, and human genetics currently being created, requiring robust, modern systems for protection and maintenance. Big data reduce healthcare costs and also improve the accuracy, speed, quality, and effectiveness of healthcare systems. Bort reported on combating influenza based on flu report by providing near real-time view [105]. Other big data initiatives were to monitor inhaler usage and reduce the risk of the asthma attack and cancer [106]. BDA can also help health insurance companies to identify fraud and anomaly in a claim, which is difficult to detect by the common transaction processing system [107]. Big data application has many values in healthcare including right care, right living, right innovation, right provider, and right value [108]. Big data can be used to population health management and preventive care as a new application of Huge Data in the future [106]. Despite the high potential of using massive data in healthcare, there are many challenges, for example, improving the available platform to better support the easy friendly package, a menu driven, data processing, and more real times. There are also other challenges in using big data in the healthcare industry including data acquisition continuity, ownership, standardized data, and data cleansing [109].

6. Analytics in supply chain

Big data create different capabilities in the supply chain that provides networks with greater data accuracy, insights, and clarity and also create a greater e-contextual intelligence shared across the supply chains. Big data are a powerful tool for solving supply chain issues and driving supply chains ahead. For example, currently, BDA techniques have applied in the retail supply chains to observe customer behaviors by accurately predicting the customer tastes and preferences. Supply chain decision makers to succeed in today's competitive markets must always seek ways to effectively integrate and manage big data sources to gain more values and competitive advantage. The effective and appropriate use of big data sources and techniques resulted in enormous improvements in processes of supply chain:

- Building agile or responsive supply chains through predicting and gaining a better understanding of the market trends and customer expectations and preferences. BDA can facilitate the real-time monitoring of supply chain and managing of data that enhance the speed, quality, accuracy, and flexibility of supply chain decision. Utilize a wide range of data from news, social media, weather data (SNEW), and events as well as direct data inputs from multiple static and dynamic data points provide the capability to predict and proactively plan all supply chain activities.

- Building reliable and intelligent supply chains through the application of Internet of Things (IoT), machine learning, and deep learning techniques in each supply chain activities. For instance, IoT can provide real-time telemetry data by the real-time monitoring of supply chain to reveal the details of production processes. Machine learning algorithms that are trained to analyze the data can accurately predict imminent machine failures. Deep learning techniques can also be used to accurately predict customers' demand and their preferences and expectations.

- Supporting the creation of sustainability in SCM. BDA undoubtedly will enhance social, environmental, and financial performance measures. For example, detailed planning for timely delivery of the product can be done by analyzing the real-time traffic data provided by the GPS that reduces production of carbon emission and the cost of fuel consumption.

- Enabling global supply chains to adopt a preventive rather than a reactive measures to supply chain risks (e.g., supply failures due to natural hazards or fabricated, contextual and operational disruptions). In a more complex global supply chain, BDA techniques can help supply chain managers to predict external future events and adopt a proactive against them.

BDA can also be applied across the end-to-end supply chain. For instance, the points of sales (POS) data on retailers provide real-time demand data with price information. It gives the signal for replenishment such as in the vendor managed inventory system. RFID data provide automated replenishment signal, automated receiving and storing information, and automated checkout data, which inform the real-time inventory status. Supplier data provide important data about suppliers and ordering processes that can help the supplier risk management and better coordination with supplier processes. Manufacturing sensor data provide real-time monitoring of manufacturing equipment and identify an inevitable problem. During the delivery process, GPS data provide real-time inventory location data and help in finding optimal routes and reducing inventory lead times and fulfillment [110].

Despite the potential use of big data, many supply chains are unable to harness the power of BDA techniques to generate useful knowledge and insights into available data for their businesses. The underlying reasons are due to the lack of ability to apply appropriate techniques for big data analysis, which result in significant cost reduction [110]. Therefore, the efforts to strengthen the BDA capabilities in supply chain are considered as an important factor for the success of all supply chains [2].

7. Conclusion and managerial implications

BDA have become an important practical issue in many areas such as SCM. There are many scopes for advancement in the application of appropriate analytic techniques in this area. As stated in previous literature [7–9], there are a variety of techniques and fundamental applications in the SCM (e.g., predictive, descriptive, and prescriptive). This chapter tries to demonstrate some of the most fundamental and recent applications of BDA within the SCM and also notice some of these techniques in SCM that are critical for managers. BDA have important applications across the end-to-end supply chain. BDA have many important applications across the end-to-end supply chain. For example, this is applied in various areas of SCM including the demand data at the sales department, retailer data, delivery data, manufacturing data, and until supplier data. BDA are also used in various supply chain activities and support them, including supplier relationship management, product design, development, demand planning, inventory, network design, production, procurement, until logistics and distribution, as well as the reverse. Applying big data sources and analytics techniques have led to many improvements in supply chain processes. Furthermore, BDA can support the development and improvement of responsive,

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reliable, and/or sustainable supply chain. BDA can able to manage and integrate huge sets of diverse data in a complex global supply chain. Many researchers have applied various techniques of BDA across different industries including the healthcare finance/banking and manufacturing. Other industries such as hospitality, technology, energy, and other service industry will also take advantage of BDA techniques. Depending on the contexts used and the strategic requirements of organizations, different techniques of BDA are applied. The culture, politics, environment, and the management team within the organization are very critical factors in decision making. Since, sufficient resources with analytic capabilities become the biggest challenges for many today's supply chain. Supply chain has to establish close and continuous links between data experts and their business function and also apply appropriate BDA techniques according to the context of their application in their decision making, processes, and activities to answer the question of how data can help drive supply chain result. Hence, mutual coordination and cooperation between different supply chain units must be established, use BDA techniques to link these units, and exist an ability to share and access data and information throughout the entire supply chain.

Author details

Saeid Sadeghi Darvazeh*, Iman Raeesi Vanani and Farzaneh Mansouri Musolu
Department of Industrial Management, Faculty of Management and Accounting, Allameh Tabataba'I University, Tehran, Iran

*Address all correspondence to: saeid.sadeghi@atu.ac.ir

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