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Chapter

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

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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):

$$C_t \left[\frac{m.u.}{year} \right] = C_p + C_s + C_i + C_r \quad (1)$$

where C_t is the total annual cost of manufacturing and keeping in stock the number of annual desired units (m.u./year); C_p 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); C_s is the total annual cost to keep in stock the necessary parts to properly serve the desired number of units (m.u./year); C_i is the total annual cost of investments needed in the specific manufacturing system (m.u./year); C_r 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 C_p can be calculated as indicated in Eq. (2):

$$C_p \left[\frac{m.u.}{year} \right] = \frac{D}{B} \cdot T_p \cdot C_{hp} \quad (2)$$

where C_p 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); T_p is the preparation time of the corresponding process (h); C_{hp} is the cost of the time of preparing the corresponding process (m.u./h).

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

$$C_s \left[\frac{m.u.}{year} \right] = \frac{B}{2} \cdot C_{sp} \quad (3)$$

where C_s 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 C_{sp} 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* C_i can be calculated as indicated in Eq. (4):

$$C_i \left[\frac{m.u.}{year} \right] = \frac{C_{et}}{y} \quad (4)$$

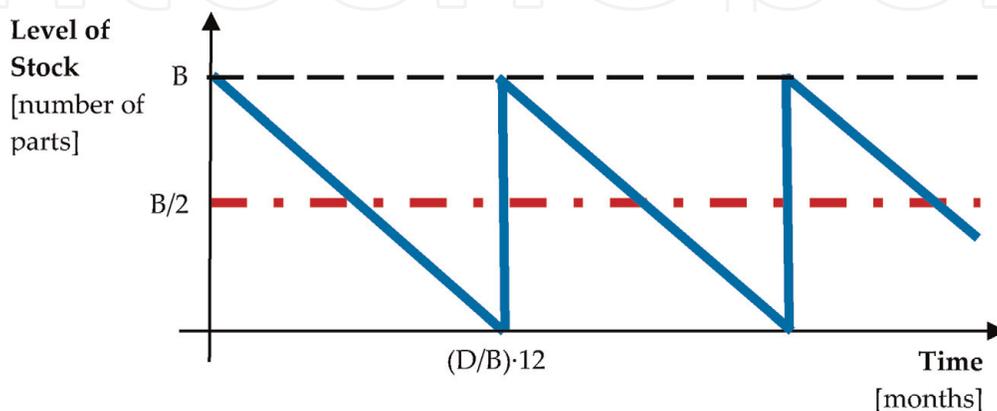


Figure 1. Evolution of stock levels taking into account the considerations set on the inventory policy. B is the size of the batches to be manufactured and D is the total annual demand, both expressed in number of parts.

where C_i is the total annual cost incurred in investments for the manufacturing system (m.u./year); C_{et} 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* C_r can be calculated as indicated in Eq. (5):

$$C_r \left[\frac{m.u.}{year} \right] = D \cdot C_d \quad (5)$$

Where C_r 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 C_d 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):

$$C_t \left[\frac{m.u.}{year} \right] = \frac{D}{B} \cdot T_p \cdot C_{hp} + \frac{B}{2} \cdot C_{sp} + \frac{C_{et}}{y} + D \cdot C_d \quad (6)$$

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)).

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

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

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

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.

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

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:

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

which, grouping terms, can be formulated as:

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

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):

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

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 B_c 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):

$$T_A \left[\frac{\text{min}}{\text{part}} \right] = \frac{Tp_A}{B_A} + Tf_A = \frac{Tp_A + Tf_A \cdot B_A}{B_A} \quad (14)$$

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)):

$$T_B \left[\frac{\text{min}}{\text{part}} \right] = \frac{Tp_B}{B_B} + Tf_B = Tf_B \quad (15)$$

where T_B is the manufacturing time per part in the case of a B process without tooling (min/part); Tf_B 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 T_p 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 B_c , 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 (B_c) between processes A and B .

In the case referred here, for batches with number of units lower than the number of parts corresponding to B_c , 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 B_c , 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.

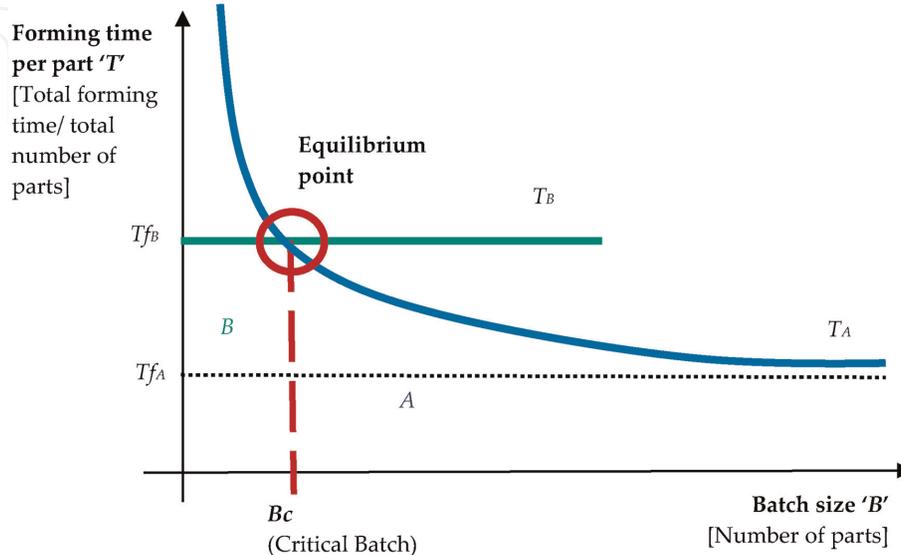


Figure 2. Forming time per part as function of the batch size for different processes (A process with tooling-rigid process-and B process not requiring a specific tooling-more flexible process.)

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):

$$Ct_A = Ct_B \iff \quad (16)$$

$$Cp_A + Cs_A + Ci_A + Cr_A = Cp_B + Cs_B + Ci_B + Cr_B; \quad (17)$$

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

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

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

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 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

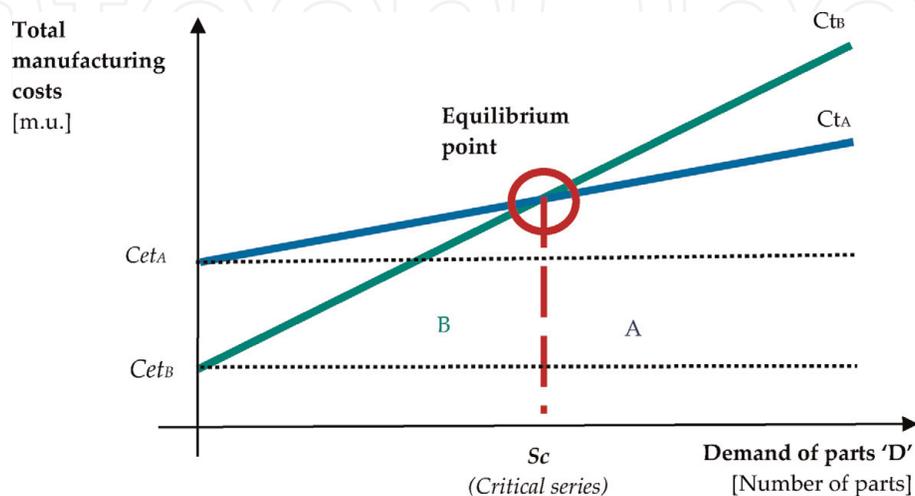


Figure 3. Total manufacturing costs as function of the size of the series for two different processes A and B . In this case, the use of tooling and equipment is assessed in both processes, although process B is contemplated to be more flexible than process A .

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

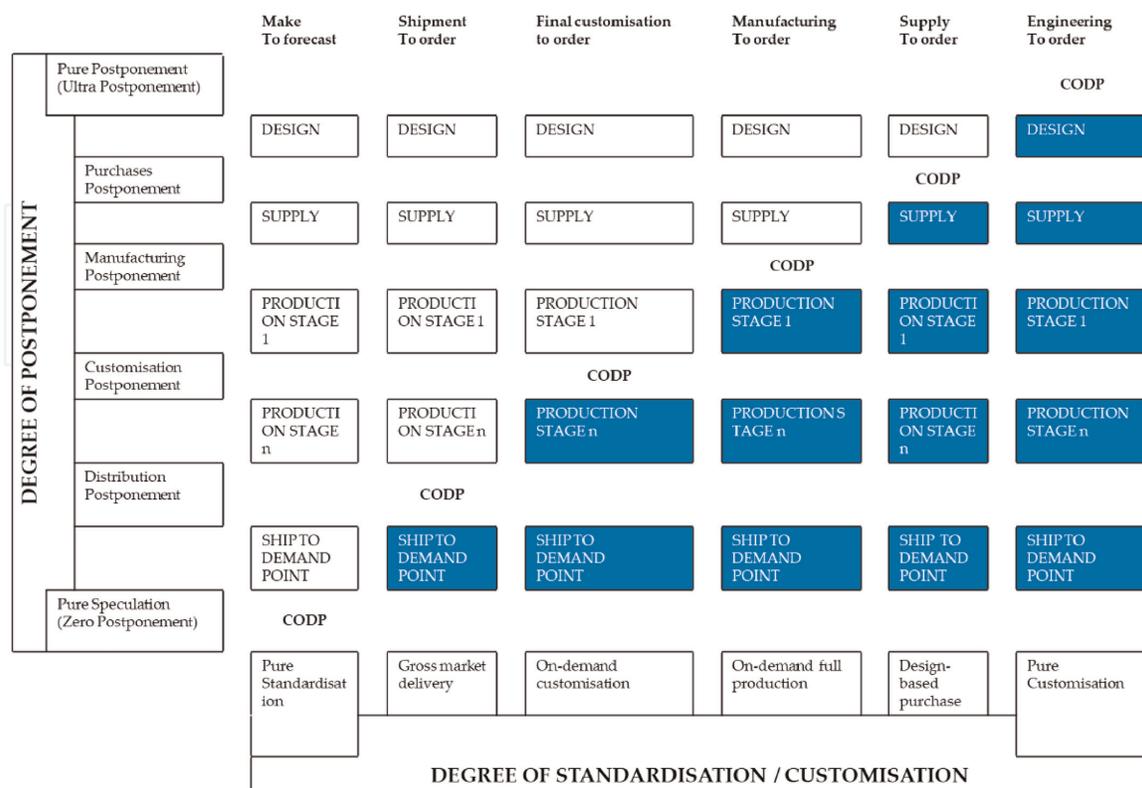


Figure 4. Schematic representation of the CODP position in different situations along the value chain. Presented in [5] and elaborated from the findings of the study of Yang et al. [8].

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 customer 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, 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):

$$B_A^* = \sqrt{\frac{2 \cdot T_{pA} \cdot Chp \cdot D}{C_s}} = \sqrt{\frac{2 \cdot 2h \cdot 30 \frac{m.u.}{h} \cdot 6000 \frac{parts}{year}}{2 \frac{m.u.}{year}}} = 600 \text{ parts} \quad (21)$$

$$\begin{aligned} Ct_A &= \frac{D}{B_A} \cdot T_{pA} \cdot Chp + \frac{B_A}{2} \cdot C_s + C_i + D \cdot Cd_A \\ &= \frac{6000 \text{ parts}}{600 \text{ parts}} \cdot 2h \cdot 30 \frac{m.u.}{h} + \frac{600 \text{ parts}}{2} \cdot 2 \frac{\text{€}}{\text{year}} \\ &\quad + 6000 \text{ parts} \cdot 0,15 \frac{m.u.}{\text{part}} + 6500 \text{ m.u.} = 8600 \text{ m.u.} \end{aligned} \quad (22)$$

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:

$$C_A = \frac{Ct_A}{D} = \frac{8600 \text{ m.u.}}{6000 \text{ parts}} = 1.43 \frac{m.u.}{\text{part}} \quad (23)$$

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)):

$$Ct_B = \frac{6000 \text{ ud}}{400 \text{ ud}} \cdot 1h \cdot 30 \frac{\text{€}}{h} + \frac{400 \text{ ud}}{2} \cdot 2 \frac{\text{€}}{\text{ano}} + 6000 \text{ ud} \cdot 2 \frac{\text{€}}{\text{ud}} + 0 = 12850\text{€} \quad (24)$$

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
T_{pB} (h/batch)	Chp_B (m.u./h)	B_B (parts)	C_{sB} (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:

$$C_B = \frac{Ct_B}{D} = \frac{12850 \text{ m.u.}}{6000 \text{ parts}} = 2.14 \frac{\text{m.u.}}{\text{part}} \quad (25)$$

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)):

$$Ct_A = Ct_B \quad (26)$$

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

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

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

$$D = \frac{6700}{1.825} = 3671.23 \text{ ud} \quad (29)$$

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 ($B_B = 400 \text{ parts}$).

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).

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

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

$$C_C = \frac{8450}{10000} = 0,845 \frac{\text{m.u.}}{\text{part}} \quad (32)$$

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**.

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

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

<i>X</i> (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*.

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

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

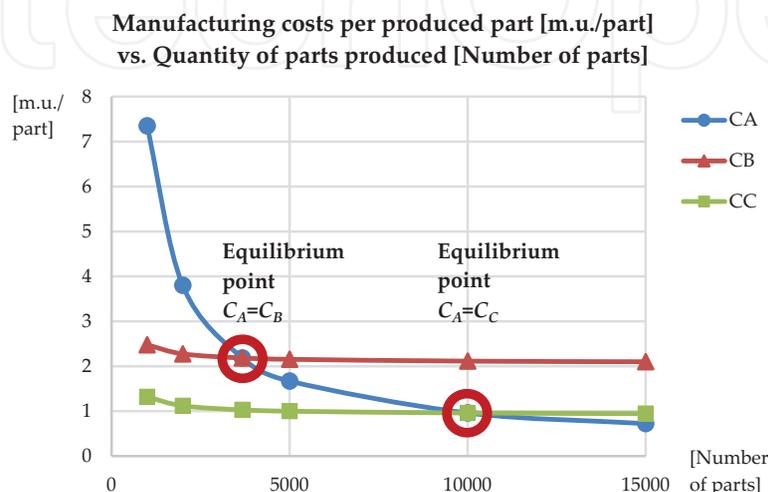


Figure 5. Costs of manufacturing per part produced as function of the number of manufactured parts by processes *A*, *B* and *C*.

these techniques is by using the 'If-Then-Else' queries supported on a rule-based 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 straightforward 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 B_c 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 S_c 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.

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