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Conventional or additive manufacturing for spare parts management: An extensive comparison for Poisson demand

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ABSTRACT

Due to the main peculiarities of spare parts, i.e. intermittent demands, long procurement lead times and high downtime costs when the parts are not available on time, it is often difficult to find the optimal inventory level. Recently, Additive Manufacturing (AM) has emerged as a promising technique to improve spare parts inventory management thanks to a 'print on demand' approach.

So far, however, the impact of AM on spare parts inventory management has been little considered, and it is not yet clear when the use of AM for spare parts inventory management would provide benefits over Conventional Manufacturing (CM) techniques.

With this paper we thus aim to contribute to the field of AM spare parts inventory management by developing decision trees that can be of support to managers and practitioners.

To this aim, we considered a Poisson-based inventory management system and we carried out a parametrical analysis considering different part sizes and complexity, backorder costs and part consumption. Moreover, we evaluated scenarios where the order-up-to level is limited to resemble applications with a limited storage capacity.

For the first time, the analysis was not limited to just one AM and one CM technique, but several AM and CM techniques were considered, also combined with different post-process treatments, for a total of nine different sourcing alternatives. In addition, the economic and technical performance of the different sourcing options were obtained thanks to an interdisciplinary approach, where experts from production economics and material science were brought together.

1. Introduction

Spare parts management is central for maintaining a high availability of production systems and is crucial when considering both economic and technical aspects. Spare parts are usually characterised by intermittent demands that are difficult to predict in terms of both quantity and frequency. Other peculiarities are long procurement lead times, a strong dependency on suppliers, and high downtime costs when the parts are not available on time. This results in considerably high costs when the wrong forecasting methods and inventory management approaches are applied (Huiskonen 2001; Hu et al., 2018).

A solution to this problem could be a transition to additive manufacturing (AM) technologies. Thanks to its short setup times and the tool-less manufacturing approach (Walter et al. 2004), spare parts can be manufactured on-demand with AM, reducing the need for high inventory levels to cover the inaccuracy of demand forecasting methods and to avoid high downtime costs. Furthermore, when AM technology is in-sourced, it reduces the dependency on suppliers, hence decreasing the risks and costs associated with supply disruptions. This is more relevant in cases of decentralised production systems, such as offshore platforms.

The basic principle of AM is that a part can be manufactured layer by layer directly from a computer-aided design (CAD) model using a combination of energy delivery and material deposition (Wong and Hernandez 2012). Particularly, based on material deposition procedures, AM technologies for metal components can be divided into two

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main groups: powder bed fusion (PBF), where a powder bed is melted or sintered layer by layer to the desired shape by a heat source, and direct energy deposition (DED), where the feedstock is deposited directly into the melt pool generated by the focused energy (Yakout et al. 2018).

Contrary to Conventional Manufacturing (CM) technologies, this production method allows the production of customized parts characterized by complex geometries in very short lead times. This is possible since AM is a tool-less manufacturing approach, with no or very limited setup times. Dealing with the possibility of producing complex parts, AM has already been implemented in aerospace, biomedical and transportation applications (Zaharin et al., 2018). Moreover, several post-process treatments (e.g., mechanical polishing, hot isostatic pressing, shot peening, annealing and T6 heat treatment) are nowadays available to couple AM with specific operating conditions (Kumbhar and Mulay 2018). Post-process treatments, in fact, increase the mechanical properties of the parts, but that comes at the expense of much higher production costs and lead times (Liu and Shin 2019; Beretta and Romano 2017).

However, the transition to AM from CM is hindered by two main barriers that complicate the identification of promising cases and may prompt a risk-averse attitude at the management level (Knofius, van der Heijden, and Zijm 2019b).

The first barrier is related to the uncertainty of the mechanical properties of the AM parts. The scarcity of real data on their failures under different operating conditions, which is also a consequence of continuous developments in terms of the range of combinations of AM technologies and post-process treatments, cannot guarantee that AM parts will withstand complex loading scenarios; this has hindered the development of failure criteria useful to predict failures (Peron et al. 2017, 2018a, 2018b; Chebat et al., 2018), thus leaving accelerated tests as the only viable alternative for estimating the mechanical properties of AM options (Razavi 2019). In such an uncertain scenario, companies would rather trust proven methods than embrace and explore the new opportunities presented by AM technologies.

The second barrier is related to high production costs, which will likely decrease in the near future, but the order of magnitude and the timing are difficult to predict (Jiang et al. 2017). Nevertheless, the increasing range of AM options, which can be identified by a combination of technologies and post-process treatments, could speed up the descent of production costs and deserve to be included in inventory management systems (Westerweel et al., 2018).

In the current paper, we aim to understand under which conditions a transition from CM to AM is economically profitable for spare parts supply. Specifically, for the first time, we consider not only the AM and CM technologies, but also their combination with post-process treatments. However, to accurately understand when a transition to AM is economically profitable, we first need to investigate how the changes in: (i) spare part application features (complexity and size of the part, backorder cost and consumption) and (ii) AM/CM features (mechanical properties, production costs and times) affect the selection of the manufacturing option (defined as the combination of CM or AM technology and post-process treatments). Moreover, it is widely known that the adopted inventory management system strongly affects the conditions making the switch to AM economically profitable; therefore, before answering the main research question, (iii) we need to understand also how the changes in inventory management system variables (review interval and the order-up-to level since herein we have adopted a periodic order-up-to level inventory management system) affect the selection of the manufacturing option.

Thus, in the following, we first aim to answer three preliminary research questions:

- *RQ1: How do the changes in spare part application features affect the selection of the manufacturing option?*
- *RQ2: How do AM/CM features affect the selection of the manufacturing option?*
- *RQ3: How do the inventory management system variables affect the selection of the manufacturing option?*

And then, the main research question:

- *RQ4: Under which conditions is a transition to an AM option economically profitable for spare parts management?*

It is worth mentioning that a decision tree analysis has also been included to answer the final question and provide general guidelines and managerial implications.

To answer the RQs, an inventory system for Poisson demand has been introduced, varying the said input parameters to carry out an exhaustive search for the manufacturing option reaching the minimum total cost. In particular, to answer RQ1, RQ2 and RQ3, a parametric analysis with 27 different scenarios has been carried out, where different spare part application features, AM/CM features and inventory management system variables have been considered. The parametric analysis is discussed in detail in Section 4. The parametric analysis has then been extended, considering now more than 1000 scenarios, to carry out a decision tree analysis: in such a way it was possible to define the conditions of applicability of AM options, supporting the managers in selecting the most profitable manufacturing option. Prior to that, a literature analysis on spare parts inventory management modelling that considers AM technologies is conducted in Section 2, while Section 3 describes the methodological framework used to support the study. The mathematical model for the inventory management system with an explanation of the input–output and decision variables is included here. Finally, Section 5 summarises the general findings, suggesting some guidelines for practitioners and defining future research.

2. Literature analysis

The complexity of spare parts management lies in their intermittent demands, which make the standard forecasting and inventory management systems ineffective in dealing with these demand patterns. Furthermore, when demands occur, the demand sizes may be highly erratic, which exacerbates the intrinsic complexity of spare parts management (Bacchetti and Saccani 2012; Huiskonen 2001).

Regarding the forecasting approaches applied to spare parts management, two main research streams can be identified. The first does not consider the factors affecting spare part consumption, thus dealing with time series as standalone data without using additional information from the service operations. This research stream includes both parametric, from the seminal contribution of Croston (1972) to its several variants (e.g., Babai et al. 2014), and non-parametric approaches, which include bootstrapping (e.g., Hasni et al., 2019) and machine learning techniques (e.g., Lolli et al., 2017). For a review on the parametric and non-parametric forecasting approaches, the reader can refer to Boylan and Syntetos (2010). The second research stream links forecasting to maintenance strategies (e.g., Van Horenbeek et al., 2013) and uses information coming from the installed base (e.g., Van der Auweraer, Boute, and Syntetos, 2019) as explanatory factors of the demand generating process.

Nevertheless, the demand forecasts of spare parts produced via AM can be linked directly to the mechanical properties achievable by means of different AM technologies and post-process treatments (Sgarbossa et al., 2020). Hence, we are interested in paying more attention to the impacts of AM on inventory management systems than to forecasting. Indeed, since spare parts are produced on demand in case of AM, the longer procurement lead times of CM can make the transition to AM profitable, despite the consequential increase of production costs. The said transition has to be evaluated in terms of cost items arising from the inventory management system that is adopted. However, even if AM constitutes a promising technology, especially towards the consolidation of parts and, more specifically, spare parts (Knofius, van der Heijden, and Zijm 2019a), only a few papers deal with the dual/multiple sourcing problem (AM/CM) in the field of spare parts management. These contributions are briefly summarised below. All of them investigate the potential benefits of the AM option and provide results under predefined inventory management systems and maintenance strategies.

Liu et al. (2014) investigated the inventory level reduction derived from the production of spare parts via AM in the aerospace sector. However, the spare parts produced via AM show disadvantages in terms of their production costs and reliability, so several authors have studied the opportunity of switching between CM and AM by means of cost-based optimisation models. In particular, Song and Zhang (2016) introduced a two-stage approach, where spare parts are first partitioned into two clusters (i.e., CM make to stock and AM make on demand); then, a continuous review policy is optimised for spare parts belonging to the first cluster. Knofius et al. (2020) proposed a single-item Markov decision process where the CM/AM dual sourcing problem arises whenever a spare part must be replaced, here with the aim of minimising the total cost function. It is worth noting that this contribution adopts for the first time failure rates specific for each selected technology. Westerweel et al. (2018) adopted a life cycle cost analysis to search for the break-even point in terms of production costs and reliability, that is, the point where the total life cycle costs of CM/AM are equal. Since lifecycle cost analysis is under a "from cradle to grave" perspective, they took under consideration the lifecycle phases from designing to exploitation (disposal costs are disregarded). Westerweel et al. (2018) explored the benefits of using AM technologies to produce military spare parts on demand, in particular when required in remote geographic locations, which would make CM unsuitable. Recently, Knofius, van der Heijden and Zijm (2019a, 2019b) developed a single-item dynamic programming model to search for the best time period to switch from CM to AM for the replenishment of spare parts. In this work, the unitary production cost via AM is supposed to decrease over time because of technological improvements, but now, dual sourcing still seems to be an effective strategy. For some examples of a holistic framework for the selection of spare parts in switching to AM, the reader can refer to Knofius et al. (2016) and Heinen and Hoberg (2019), both of which operate under specific inventory management systems and maintenance strategies. In sum, the lowest cost sourcing alternative is a relevant goal to reach also in spare parts applications because it is a specific application field of the dual/multiple sourcing problem (e.g., Minner (2003)).

As already highlighted, the inventory management system and the maintenance strategy have to be fixed to evaluate the opportunities of a transition to AM because they affect the inventory cost and, in turn, the lowest cost alternative. Moreover, the spare parts produced via AM may be obtained by means of different technologies, as well as subjected to different post-process treatments. Although this increasing range of AM options can stimulate further investigations on the profitability of switching to AM, it introduces increased complexity in modelling the demand into the inventory management system for all the AM options, that, to the best of our knowledge, no one has tried to address so far. Thus, in this paper, we aim to fill this gap. Specifically, we aim to understand under which conditions the transition to AM is economically profitable considering the combination of several AM and CM technologies with different post-process treatments.

3. Methodological framework

This paper investigates how CM and AM technologies impact the spare parts sourcing problem. Several application scenarios have been analysed to investigate when one group of technologies is better than the other (CM vs. AM) and which specific option (technology and post-process treatment) is the best one, here varying spare parts consumption, their size and complexity and their criticality in terms of backorder cost based on where they are used. In particular, the study is applied to a single material (316L stainless steel) and to three different part sizes, referred to as 'small' (Volume = 100 cm^3, Surface Area = 150 cm^2), 'medium' (Volume = 500 cm^3, Surface Area = 300 cm^2) and 'large' (Volume = 1000 cm^3, Surface Area = 600 cm^2), but its formulation is independent from the material and part size considered. It is assumed that the part under analysis is currently produced by casting and subjected to polishing as a post-process treatment.

Dealing with CM, three main technologies are considered, namely casting (C), wrought (W) and forging (F). As for AM is concerned, we consider the most common PBF and DED techniques, that are selective laser melting (SLM) and laser engineered net shaping (LENS). Although forging represents a subset of the wrought group, it stands out in terms of mechanical properties, and hence it has been considered as a separate group. In addition, the use of post-process treatments such as polishing (P), annealing (A) and hot isostatic pressing (HIP) to improve the mechanical properties has also been considered. It is worth mentioning that the geometrical complexity achievable by the aforementioned technologies is different: simple parts, such as connecting rods, can in fact be manufactured indistinctly with all three CM groups, while complex parts, such as an engine head, can only be manufactured using casting technologies. AM technologies, on the contrary, can print a wide range of parts, even very complex ones, due to their flexibility and advanced solutions. In the light of this, in the following we distinguish between simple and complex parts based on the CM technologies that can be used to manufacture them (AM technologies can indistinctly manufacture simple and complex geometries): simple parts are the parts that can be manufactured by all three CM technologies (casting, wrought and forging), while casting is the only CM technique that can be used to produce complex parts.

In Fig. 1, a methodological framework is defined to describe the structure of the current study. Each application scenario is defined by a set of features *(spare parts application features),* such as the mean time to failure (MTTF) of the part, holding cost, backorder cost and part size and complexity. For each scenario, each sourcing alternative is evaluated using a mathematical model for a spare part inventory management system.

Each sourcing alternative is identified by combining the CM or AM technology and post-process treatments (manufacturing option) and procurement lead time. In the case of CM, the procurement lead time could vary based on the supplier, while in the case of AM the procurement is on demand. The sourcing alternative has been compared not only between CM and AM groups, but also among CM and AM technologies and post-process treatments. As the literature analysis has shown, CM and AM options are characterised by some features that could affect the sourcing decision and could be grouped into *mechanical properties,* in this case the fatigue strength, which is expressed by the MTTF, and the *economic and technological parameters*, such as their production costs, including both technology and post-process treatments.

Based on these input parameters, a periodic inventory management system is optimally set (i.e., order-up-to level), and the total cost is estimated for each sourcing alternative, varying the review period and the inventory capacity as *decision variables and constraints*. Although the order-up-to level will be defined to minimise the total cost, an external factor that could impact the sourcing decision is the inventory capacity. This limitation to the order-up-to level has been considered as a constraint. For example, in the case of remote facilities such as offshore platforms, there is often not enough space to stock all the spare parts needed under optimal conditions. In those cases, the order-up-to level could be even null, thus affecting the sourcing decision (Westerweel et al., 2020).

3.1. Inventory management system

The main element of the framework is the periodic inventory management system that is used to compare the different sourcing policies and to investigate the features identified in the previous section.

Table 1 lists our system input parameters, while Table 2 contains the

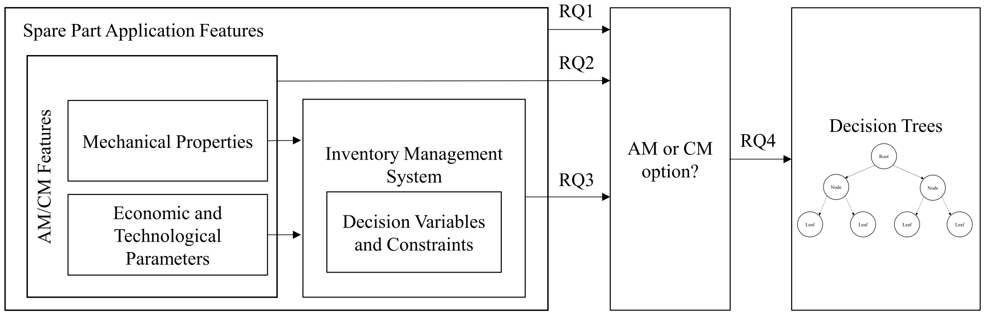

Fig. 1. Framework of the study.

Table 1
Parameters.

Parameter	Description	Unit measure
$i = 1,\ldots,n$	Manufacturing option: technology and post-process treatment.	
Spare parts application features		
$MTTF_{cast}$	Mean time to failure of the casting technology; this is the reference value to compute $MTTF_i$ $i = 1,\ldots,n$.	[*time*]
Size	Spare part's size affecting $c_{p,i}$.	Categorical
Complexity	Spare part's complexity; impacts on the feasible technologies for the spare part.	Categorical
h	Holding rate.	
c_b	Unitary backorder cost.	[€ /*unit*]
Mechanical properties		
r_i	$\frac{MTTF_i}{MTTF_{cast}}$	
$MTTF_i$	Mean time to failure of i (Equation (1)).	[*time* /*unit*]
λ_i	Failure rate of i (Equation (2)).	[*unit* /*time*]
Economic and technological parameters		
L_i	Procurement lead time of i.	[*time*]
$c_{p,i}$	Unitary production cost of i.	[€ /*unit*]

Table 2
Decision variables, constraints and costs of the inventory management system.

Decision variables		
T_i	Review period of i.	[*time*]
S_i	Order-up-to-level of i.	[*unit*]
Constraints		
S_{max}	Maximum order-up-to level.	[*unit*]
Costs		
C_h	Holding cost each time unit.	[€ /*time*]
C_b	Backorder cost each time unit.	[€ /*time*]
C_p	Production cost each time unit.	[€ /*time*]

variables, constraints and costs of the inventory management system.

The size feature cited in the previous section impacts the unitary production cost $c_{p,i}$, where the bigger the item, the higher the unitary cost $c_{p,i}$. Contrary to the size feature, the complexity feature impacts in a limited way the unitary production cost: in this paper we have distinguished between simple and complex parts based on the manufacturing technologies that can be used (i.e., complex products can only be produced using casting or AM technologies, while simple products are produced either by all three CM technologies considered or by AM technologies), and the difference in the unitary production cost for the different technologies is lower than that imposed by the size feature. For the estimation of each $MTTF_i$, a part produced using casting and subjected to polishing as a post-process treatment is assumed to be the reference.

Each mean time to failure $MTTF_i$ is obtained from the reference $MTTF_{cast}$ as follows:

$$MTTF_i = r_i \cdot MTTF_{cast} \tag{1}$$

The procedure to compute r_i is described in Section 3.2.

From each $MTTF_i$, a failure rate λ_i is then obtained:

$$\lambda_i = \frac{1}{MTTF_i} \tag{2}$$

where λ_i is used in Equations (3)–(7).

Since $MTTF_i$ is the reliability data achievable by means of the accelerated tests, the Poisson distribution function is a natural candidate to model the demand. Thus, the inventory management system adopted is inspired by that in Babai et al. (2011), which is adapted to the multiple technology case:

- Their system is continuous, and an order is placed after each demand. Our system is periodic, and thus, each order satisfies the demand of $(T_i + L_i)$ periods. The lead time L_i is deterministic, and the main variable to be optimised is S_i, assuming for CM three values for the period T_i (4, 8 and 12 weeks), while the order for AM can be placed every L_i periods.
- In their system, each demand event results in a different number of demanded items following a Poisson distribution. Our system deals with a single equipment failure; therefore, each demand event results in demand for a single item.
- In their system, only holding costs C_h and backorder costs C_b are evaluated. Our system considers the production costs C_p as well.

Then, the system optimisation proceeds as follows:

1. A CM or AM option, that is, technology and its post-process treatment, is selected.
2. If a CM option was selected, then T_i is fixed and assumed to be $T_i \leq L_i$.
3. If an AM option was selected, then $T_i = L_i$.
4. S_i is optimised following Equations (3)–(7).

Following this procedure, different optimal values for S_i can be found by choosing different sourcing alternatives and T_i.

Given the stochastic demand y, the optimisation problem, after the CM/AM option and T_i have been identified, is as the following:

$$min\ C_{tot} = min\ \left(C_h + C_b + C_p\right) \tag{3}$$

$$min\ h \cdot c_{p,i} \cdot \sum_{y=0}^{S_i-1} (S_i - y) \cdot P_{\lambda_i, T_i+L_i, y} + c_b \cdot \sum_{y=S_i+1}^{\infty} (y - S_i) \cdot P_{\lambda_i, T_i+L_i, y} + \lambda_i \cdot c_{p,i} \tag{4}$$

s. t.

$$P_{\lambda_i, T_i+L_i, y} = \frac{(\lambda_i (T_i + L_i))^y\ e^{-\lambda_i (T_i+L_i)}}{y!} \qquad i = 1, \ldots, n \tag{5}$$

$$0 \le S_i \le S_{max} \tag{6}$$

$$S_i \in \mathbb{N} \tag{7}$$

(3) minimises the time unit costs; it is rewritten in (4) where:

- C_h is the average number of units in stock $\sum_{y=0}^{S_i-1}(S_i - y)\cdot P_{\lambda_i,T_i+L_i,y}$ during the coverage time $(T_i + L_i)$ multiplied by the holding cost $(h \cdot c_{p,i})$, which is proportional to the unitary production cost $c_{p,i}$.
- C_b is the average number of units in backorder $\sum_{y=S_i+1}^{\infty}(y - S_i)\cdot P_{\lambda_i,T_i+L_i,y}$ during the coverage time $(T_i + L_i)$ multiplied by the unitary backorder cost c_b. A backorder takes place each time a demand cannot be met by the stocked units.
- C_p is the unitary production cost $c_{p,i}$ multiplied by the failure rate λ_i, which is the expected number of demands during a period.

(5) computes the probability that y failures take place during $(T_i + L_i)$ using a Poisson distribution with $\lambda_i(T_i + L_i)$ as the expected demand.
(6) imposes a maximum order-up-to level S_{max}.
(7) imposes S_i discrete.

3.2. Mechanical properties

The mechanical properties of a part are what determine its reliability characteristics, and, in particular, it is fundamental to characterise the reliability of the parts produced in AM technologies compared with those made in CM technologies to understand the impact of AM on the demand for spare parts. In other words, it is important to know if the transition to AM parts leads to a higher demand for spare parts because of a lower reliability or vice versa.

To do so, we have leveraged on accelerated tests to obtain these parameters, and, among the different types of accelerated life testing (such as usage rate acceleration and overstress acceleration), we have leveraged on the fatigue strength of laboratory specimens. In fact, thanks to the link between the MTTF of the spare part in the specific scenario under analysis and the fatigue strength of laboratory specimens, it is possible to go back to the reliability of the parts produced in AM technologies from the fatigue strength of laboratory specimens. By comparing the fatigue strength of laboratory specimens produced in AM with those produced in CM, each of them combined with the post-process treatments, it is thus possible to compare their reliability. Therefore, we carried out an extensive literature analysis on papers dealing with the fatigue behaviour of AM materials (Zhang et al, 2017, 2018, 2019; Cutolo et al., 2019; Solberg et al., 2019; Yadollahi and Shamsaei 2017; Shrestha et al. 2019; Smith et al. 2017, 2019; Spiierings et al. 2013; Huang et al., 2019), CM materials (Mohammad et al., 2012; Gibbs et al., 2016; Gordon et al., 2019; Pegues et al., 2017; Vázquez Jiménez et al., 2017; Tan et al., 2017; Mendez 1999; Okazaki 2012; Negru et al., 2013; Kwon et al., 2001; Natsume et al., 2010; Yuan et al., 2016; Agarwal et al., 2007), and both AM and CM materials (Mower and Long 2016; Blinn et al., 2018; Davies et al. 2017). Assuming the slope of the fatigue curves to be independent of the technology adopted but to be only a material property, for every combination of AM and CM technologies and post-process treatments, the MTTF ratios can be obtained as follows:

1) Determine the average fatigue strength, σ_{av}, of the considered CM technology at a certain number of cycles N^* (Fig. 2a).
2) Use the average fatigue strength, σ_{av}, of the CM technology as an input in the fatigue curves of the considered AM technology to determine the average number of cycles to failure, N_{av} (Fig. 2b).
3) Determine the MTTF ratio r_i as the ratio between the average number of cycles to failure for the considered AM technology, N_{av}, and the number of cycles set at the beginning of the procedure, N^*.

Thus, we have identified the ratio between the MTTF obtained using different AM and CM technologies and by varying the post-process treatments.

Moreover, it is worth mentioning that, contrary to CM parts where the technologies are very well established, a definitive mechanical characterisation of AM parts is far to be reached due to the continuous technological developments of the AM technologies. Therefore, the same MTTF ratios for AM technologies have been recalculated considering only the data published over the last three years ("Recent 3 years

Table 3
MTTF ratios r_i for the two different data set.

Manufacturing options	$r_i = \frac{MTTF_i}{MTTF_{cast}}$	
	Entire data set	Recent 3 years data set
Casting + Polishing (C + P)	1	
Wrought + Polishing (W + P)	2.63	
Wrought + Polishing + Annealing (W + P + A)	2.50	
Forging + Polishing	5.54	
Forging + Polishing + Annealing (F + P + A)	5.05	
SLM	0.48	0.73
SLM + Polishing (SLM + P)	5.21	6.93
SLM + Polishing + HIP (SLM + P + HIP)	6.80	10.00
LENS + Polishing (LENS + P)	1.13	1.25

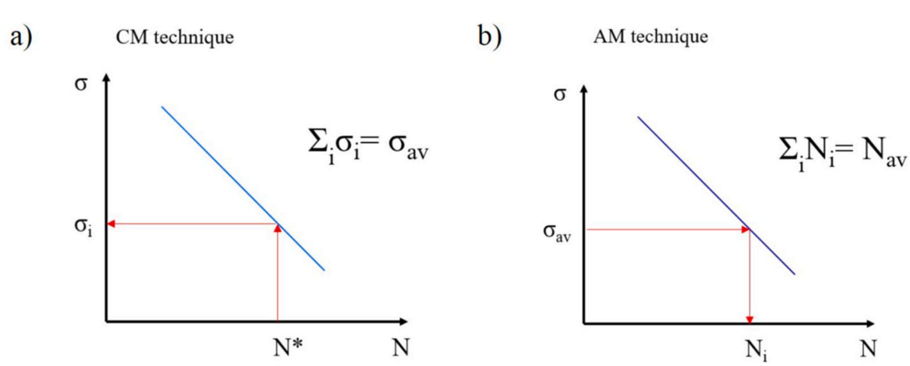

Fig. 2. Schematic representation of the determination of average fatigue strength, σ_{av}, of the considered CM technology (a) and of average number of cycles to failure, N_{av}, of the considered AM technology (b).

data set" in Table 3), and the parametric analyses that will be described in Section 4 have been carried out considering both ratios to provide an understanding of how much the technological improvements of AM can impact the implementation of such technologies in spare parts inventory management. In the following, what we will refer to "entire data set" to indicate that the MTTFs were measured considering the accelerated tests carried out from the introduction of each AM option, whereas to "recent 3 years data set" indicates that the MTTFs were measured using the accelerated tests performed only in the last three years.

3.3. Economic and technological parameters

Then, thanks to interviews with researchers and experts in AM and CM, we have collected the *economic and technological parameters* needed for the model. Particularly, we interviewed the five organizers of the "First European Conference on the Structural Integrity of Additively Manufactured Materials" (ESIAM 19) that was held in Trondheim in September 2019 under the patronage of, among others, NTNU. We decided to interview the organizers of the ESIAM 19 conference due to their renowned knowledge of CM and AM technologies and also due to the possibility to bring them together in a room in order to have an open discussion about the production cost of CM, production time and cost of AM and post-process treatments. At the end of this process (that lasted about 2 h), the experts provided us with value ranges of the aforementioned parameters, and in our analyses we used the mean values.

The value ranges of the production cost and production time of AM are reported in Table 4, together with the production cost of CM, while the cost and time of the post-process treatments are given in Table 5, and they are independent of the production process. It is worth mentioning that polishing is a surface operation, while annealing and HIP depend on the volume of the part. For CM, we are not considering the variable production time because it typically depends on several other factors, such as the setup time, batch sizes, production plans and others. We assume three representative values for the procurement lead time, such as four, eight and twelve weeks. For AM technologies, instead, because they produce the part on demand, the procurement lead time will be equal to the total production time, including the time for printing the part and for the post-process treatment.

Based on these economic and technological parameters, we have estimated the production cost and procurement lead time for three different part sizes, referred to as 'small' (Volume = 100 cm^3, Surface Area = 150 cm^2), 'medium' (Volume = 500 cm^3, Surface Area = 300 cm^2) and 'large' (Volume = 1000 cm^3, Surface Area = 600 cm^2). The values have been rounded up to make the input data simpler, more comparable and more readable; they are reported in Table 6.

4. Parametric analysis and discussion

As mentioned in the introduction, a parametrical analysis has been carried out to answer the four research questions. In particular, to answer the first three RQs (i.e., "how do the changes in spare part application features affect the selection of the manufacturing option? (RQ1)", "how do AM/CM features affect the selection of the manufacturing option? (RQ2)" and "how do the inventory management system variables affect the selection of the manufacturing option? (RQ3)"), the inventory management system has been applied to 27 scenarios of spare part applications based on the three sizes of the analysed part (small, medium and large), three MTTF values and three backorder costs. The parametric analysis has then been extended to more than 1000 scenarios to answer the last RQ (i.e., "under which conditions is a transition to an AM option economically profitable for spare parts management?"). Here, a decision tree analysis has also been included to provide general guidelines and managerial implications.

Starting with the first parametrical analysis (i.e., that used to answer the first three RQs), the inventory management system has been applied to 27 scenarios of spare part applications based on the three sizes of the analysed part (small, medium and large), three MTTF values and three backorder costs.

The reference mean time to failure, $MTTF_{cast}$, is considered by the means of three different values (using calendar weeks), corresponding to one failure per year ($MTTF_{cast}$= 52 weeks), one failure every two years ($MTTF_{cast}$ = 104 weeks) and one failure every three years ($MTTF_{cast}$ = 156 weeks).

The three values assumed for the unitary backorder cost c_b (i.e. 1000, 26000 and 51000 €/unit) well cover three possible situations, and they mainly depend on the cost of production losses, which can be very high, up to several thousand euros per hour, and on part criticality for system operations and procurement. A low value is expected when the part or the system where it is installed are not critical or when there is a redundancy in the system. The medium value is related to cases when the part is critical and its shortage causes production losses; in these cases, it is typical that the part must be bought urgently, so at a higher price while the system is not producing. The high value of the unitary backorder cost is when the part is not available on the market so with a long procurement lead time and/or when the part is particularly critical for the system thus leading to high production losses in the case of unavailability.

The complexity of the part is considered by assuming that all three CM technologies (casting, wrought and forging) can manufacture simple parts, while casting is assumed to be the only useable method to produce complex parts. All the AM technologies can produce complex parts, considering that this is one of their intrinsic characteristics. Finally, the holding cost h is typically very high for spare parts. For this reason, it has been assumed a yearly value of 30%, that corresponds to 0.58% weekly basis (Azzi et al., 2014).

For each scenario, 15 CM and 4 AM sourcing alternatives are considered. The CM sourcing alternatives are based on five CM options: cast and polishing (C + P), wrought and polishing (W + P), wrought and polishing and annealing (W + P + A), forging and polishing (F + P) and forging and polishing and annealing (F + P + A), along with three procurement lead times: four, eight and twelve weeks. The AM sourcing alternatives are based only on the four manufacturing options (SLM, SLM + P, SLM + P + HIP, LENS + P), while the procurement lead time depends on the size of the part because AM is considered on-demand supply.

For each of these sourcing alternatives, which are characterised by specific mechanical properties ($MTTF_i$) and economic and technological parameters ($c_{p,i}$, L_i), the inventory management system defines the optimal order-up-to level S_i, which minimises the total cost. In the case of CM, three values for the review period are considered for each sourcing alternative: four, eight and twelve weeks, which means that the inventory level is reviewed every one, two or three months. For AM, the review period is equal to the procurement lead time. Appendices A, B, C and D report all the results.

Table 4
Production cost and the time of AM and CM technologies.

	Additive		Conventional		
	SLM	LENS	Casting	Wrought	Forging
Production time (cm^3/s)	0.0050–0.0055	0.0050–0.0060	–	–	–
Production cost per volume (€/cm^3)	1.20–1.40	1.20–1.30	0.045–0.05	0.045–0.055	0.04–0.065

Table 5
Cost and the time of the post-process treatments.

<table>
<tr><th></th><th>Polishing (P)</th><th colspan="3">Annealing (A)</th><th colspan="3">HIP</th></tr>
<tr><th></th><th></th><th>V < 250 cm^3</th><th>250≤V ≤ 750 cm^3</th><th>V > 750 cm^3</th><th>V < 250 cm^3</th><th>250≤V ≤ 750 cm^3</th><th>V > 750 cm^3</th></tr>
<tr><td>Process Time</td><td>5.0–7.0 s/cm^2</td><td>3.0–3.3 h</td><td>3.5–4.2 h</td><td>3.7–4.1 h</td><td>3.3–3.6 h</td><td>4.5–4.8 h</td><td>3.0–4.0 h</td></tr>
<tr><td>Production Cost per process time (€/h)</td><td>90–110</td><td colspan="2">20–25</td><td>22.5–27.5</td><td colspan="2">25–30</td><td>27.5–32.5</td></tr>
</table>

Table 6
Technology-specific parameters.

<table>
<tr><th>Size</th><th>Parameters</th><th colspan="4">Additive</th><th colspan="5">Conventional</th></tr>
<tr><th></th><th></th><th colspan="3">SLM</th><th>LENS</th><th>Casting</th><th colspan="2">Wrought</th><th colspan="2">Forging</th></tr>
<tr><th></th><th></th><th colspan="2">P</th><th>–</th><th>P</th><th>P</th><th>P</th><th>P + A</th><th>P</th><th>P + A</th></tr>
<tr><th></th><th></th><th>HIP</th><th>–</th><th>–</th><th>–</th><th></th><th></th><th></th><th></th><th></th></tr>
<tr><td>small</td><td>L_i</td><td colspan="4">0.1</td><td colspan="5">4, 8, 12</td></tr>
<tr><td></td><td>$c_{p,i}$</td><td>250</td><td>150</td><td>130</td><td>150</td><td>30</td><td>30</td><td>100</td><td>30</td><td>100</td></tr>
<tr><td>medium</td><td>L_i</td><td colspan="4">0.2</td><td colspan="5">4, 8, 12</td></tr>
<tr><td></td><td>$c_{p,i}$</td><td>825</td><td>700</td><td>650</td><td>675</td><td>80</td><td>80</td><td>160</td><td>80</td><td>160</td></tr>
<tr><td>large</td><td>L_i</td><td colspan="4">0.4</td><td colspan="5">4, 8, 12</td></tr>
<tr><td></td><td>$c_{p,i}$</td><td>1500</td><td>1400</td><td>1300</td><td>1350</td><td>150</td><td>150</td><td>250</td><td>150</td><td>250</td></tr>
</table>

All the experimentations have been carried out in MatLab®. In particular, the decision trees (sections 4.41 and 4.4.2) have been implemented through the Statistics and Machine Learning Toolbox™.

4.1. AM vs. CM for spare parts inventory management system

The results of the parametric analysis, reporting the total inventory management cost, are gathered in the following figures (Fig. 3 for $c_b = 1000\ €/unit$; Fig. 4 for $c_b = 26000\ €/unit$; Fig. 5 for $c_b = 51000\ €/unit$) for different part characteristics (size and $MTTF_i$) and for different sourcing alternatives. The order-up-to level is optimised for three review periods for the case of CM options and on demand for the AM one. See Appendices A, B and C for the exhaustive tables of the results of all the scenarios.

It can be seen that F + P parts and SLM polished with/without HIP treatment (SLM + P and/or SLM + P + HIP) represent the cheapest solutions for CM and AM technologies, respectively.

The first outcome is that the answers to the first two research questions need to be combined to obtain a clear overview. The best solutions depend on a combination of the effects of each single element of the methodological framework.

The main limitation of the AM options relies on their features, such as high production costs compared with CM options. This aspect is limited when, including the application features, the part size is small when c_b is low and when MTTF is high. In particular, these last two conditions provide the possibility to leverage the 'print on demand' approach provided by the AM options. In fact, for the conditions mentioned, the optimum S_i for SLM + P and SLM + P + HIP is equal to 0, that is, no parts are stored (see Appendix C). However, when the part is simple—namely, all the CM options can be used to manufacture it—F + P always represents the cheapest solution. Contrarily, when the part is complex, that is, it can be manufactured only using casting, AM options (SLM + P and/or SLM + P + HIP) often represent the cheapest solution. In particular, the convenience of using AM as spare parts sourcing alternative increases reducing the size of the part and the unitary backorder cost, for higher MTTF, but also combined with AM/CM feature as high CM procurement lead times. In these cases, the higher production cost of the AM options is compensated not only by the possibility of leveraging the 'print on demand' approach, but also by their higher reliability, as shown from the MTTF ratios.

The effect of mechanical properties, as AM/CM feature, specifically the effect of an increased reliability, is even more evident if we consider the AM technological improvements by evaluating the MTTF ratios and consider only the data obtained over the last three years (Table 3). It is clear that the more recent data are characterised by the best mechanical performances because of the better knowledge of the different AM technologies and of a wider know-how concerning the optimum process parameters to be used to reduce defectiveness. By considering the MTTF ratios based on recent data (Appendix B), F + P and SLM + P and SLM + P + HIP still remain the cheapest solutions for the CM and AM options, respectively, but F + P is no longer always the cheapest solution. In fact, when combining some spare part application features (small part size, MTTF = 156 and $c_b = 1000$ €/unit), F + P is no longer the cheapest solution: SLM + P + HIP takes its place (except for L = 4 and T = 4), followed by SLM + P (except for L = 4 and T = 4 and 8).

4.2. Impact of inventory management system variables

Regarding the third research question, an increase in the review period correlates with an increased total inventory management cost. This, however, affects the results in a marginal way compared with the factors analysed in the previous subsection. An important aspect worth investigating is the limited inventory capacity, which is expressed in this model by the maximum order-up-to level, S_{max}. Some contributions in the literature have discussed the application of AM as a solution for spare parts management in remote facilities with limited storage capacity, such as offshore platforms (Westerweel et al., 2020). In these situations, the order-up-to level might be limited to one or even no spare parts stocked for each part under analysis.

We studied the impact of this external factor limiting the inventory capacity, or the maximum order-up-to level S_{max} , to 0 and 1. We conducted the analysis by considering the MTTF ratio, which was estimated using the data from the last three years to have a more recent and updated overview. The results are reported in Appendix D. Fig. 6 depicts the total inventory management costs for a specific case, where $S_{max} = 1$ and $c_b = 1000\ €/unit$.

In the case of no storage capacity available ($S_{max} = 0$), AM options are always the most cost-effective solutions, particularly SLM + P and, above all, SLM + P + HIP. This is aligned with the results reported in the literature and is because of the high backorder cost of CM options, even when the backorder unitary cost is low.

The same conclusions are valid when the storage capacity is limited

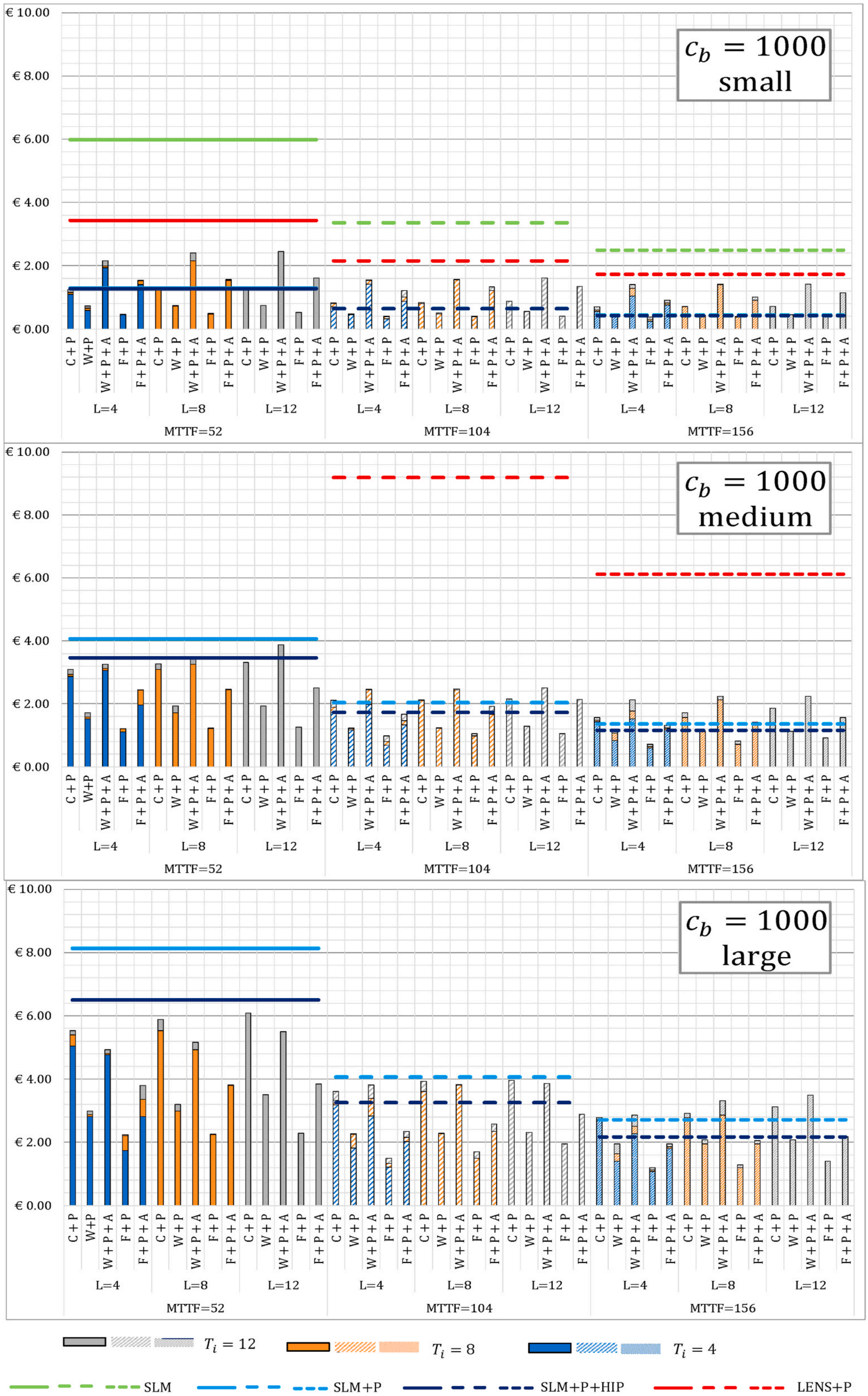

Fig. 3. Spare parts inventory management costs for different part size and reliability and of different CM review periods and procurement lead times considering the entire data set for MTTF ratio. c_b is 1000 €/unit.

to a value of 1 and the unitary backorder cost is high ($c_b = 26000$ €/*unit*; $c_b = 51000$ €/*unit*), except when the part is medium and/or large and simple, in which cases F + P can be even more convenient than SLM + P and SLM + P + HIP for a high MTTF, here depending on the procurement lead time and on the revision period of the CM options.

In the case of $c_b = 1000$ €/*unit*, the results are instead strongly affected by a combination of the spare part application features and AM/CM features (Fig. 6). For complex parts, i.e. parts that can only be produced by casting, all the AM options are cheaper than C + P when the part size is small; with an increase in the part size, SLM and LENS + P

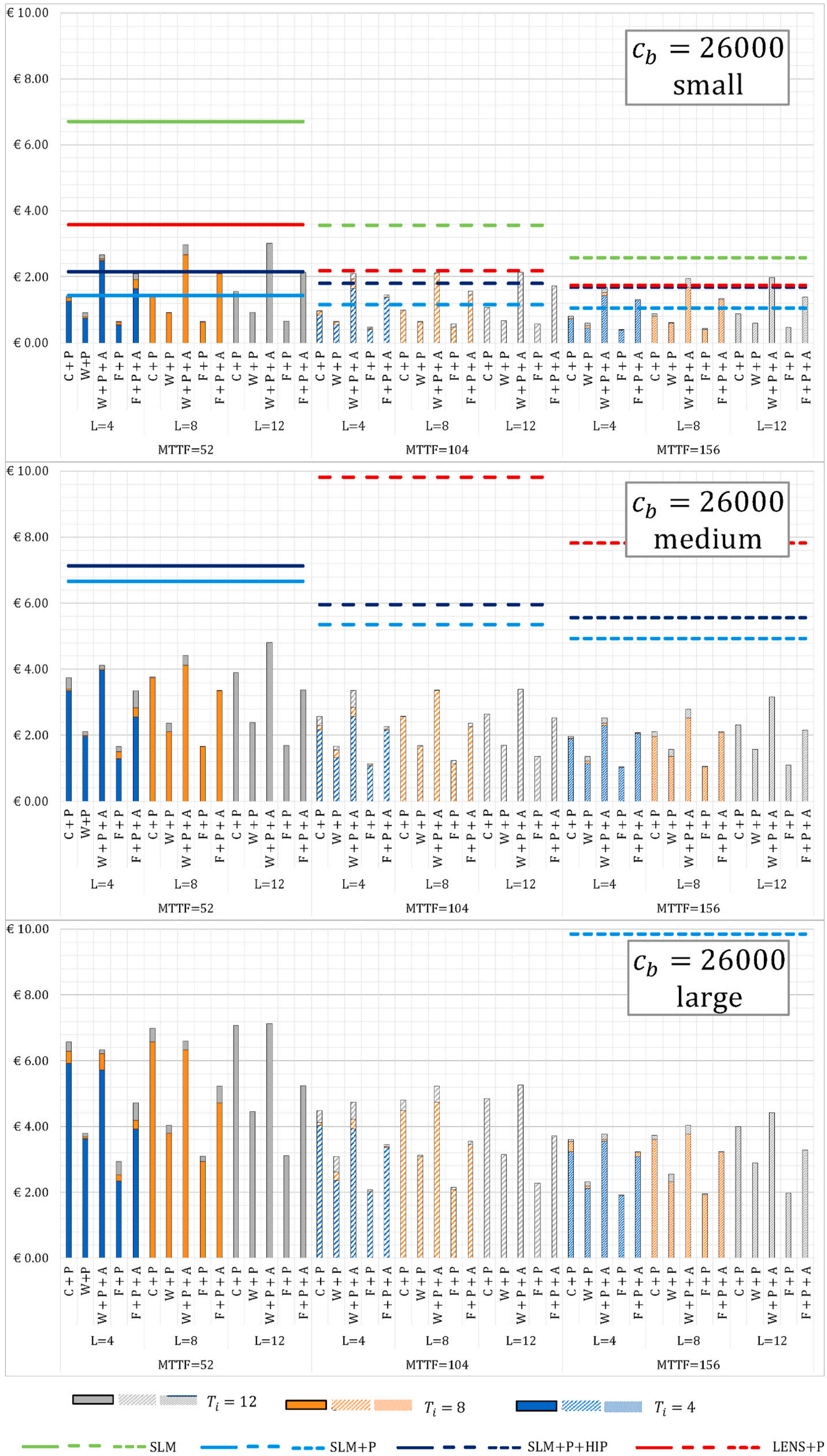

Fig. 4. Spare parts inventory management costs for different part size and reliability and of different CM review periods and procurement lead times considering the entire data set for MTTF ratio. c_b is 26000 €/unit.

becomes more expensive than C + P when there is a decrease in procurement lead time and of the review period. For simple parts, instead, F + P is always cheaper than SLM and LENS + P, while a comparison with SLM + P and SLM + P + HIP depends on the spare part application features and AM/CM features. The SLM + P + HIP option is always the cheapest AM solution, and when the part is small—because the unitary production cost is low—it is always the best solution, except when the review period is short, where in such cases, F + P is the most cost-

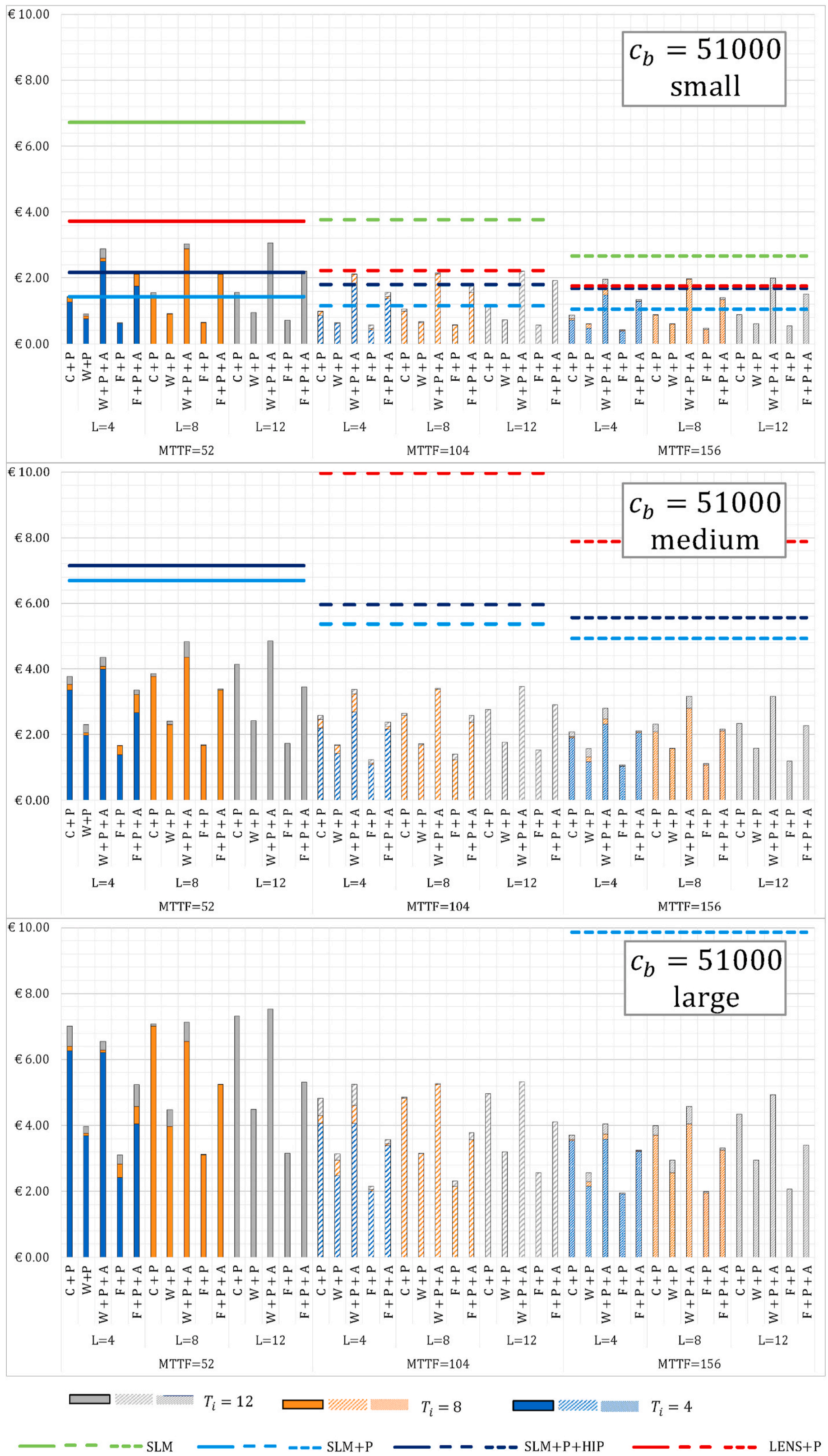

Fig. 5. Spare parts inventory management costs for different part size and reliability and of different CM review periods and procurement lead times considering the entire data set for MTTF ratio. c_b is 51000 €/unit.

effective solution. When increasing the part size, F + P is the most cost-effective solution, even with longer review periods.

In conclusion, the AM solution is the best option when there is a limitation in spare parts inventory capacity. In this situation, the complexity and size of the part, hence its production cost, and the review period and procurement lead time have a significant effect on the selection of the best sourcing alternative.

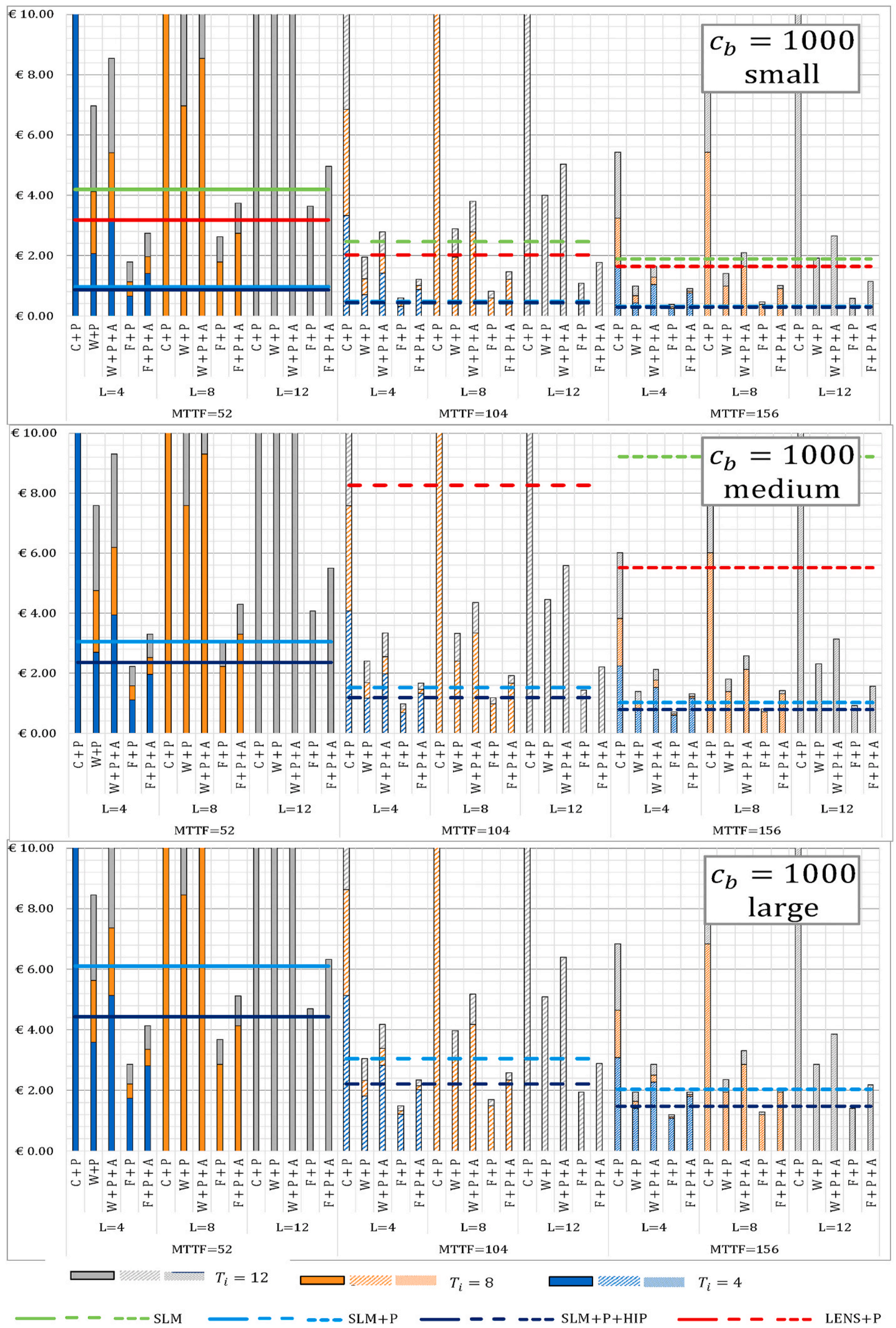

Fig. 6. Spare parts inventory management costs as Fig. 3 with limited.$S_{max} \leq 1$

4.3. Threshold cost analysis

From the previous analysis, the AM production cost impacts the final decision of using AM options instead of CM ones the most. Thus, we have extended our study on economic and technological parameters by including an analysis of the production costs. For each scenario, we calculated the ratio between the value of the AM production cost that makes the AM option comparable with those based on the CM options and the current AM production cost. For CM options, we considered only casting and forging, both with polishing as post-process treatments, because they are the best solutions for complex and simple parts, respectively.

Fig. 7 shows the box-and-whisker plot from the analysis. The minimum and maximum values are indicated by the whiskers depicted for each box. The first and third quartiles are the limits of the boxes, while the median and mean are, respectively, represented by the line and the cross within each box. The black horizontal line indicates when the ratio is equal to 1. If the values are over this line, it means that the AM option is already the most cost-effective, while if the values are lower than 1, it means that the AM production cost should be up to the ratio to make AM the most suitable option.

The general results are in line with those obtained in previous sections. Here, the SLM and LENS + P options are not suitable alternatives because they require a substantial reduction of cost, from 60% to 90%, which is not realistic and foreseeable in the near future. Concerning SLM + P and SLM + P + HIP, their applicability depends mainly on the complexity of the part. For simple parts that can be produced by forging, most of the scenarios show that a reduction in the production cost should

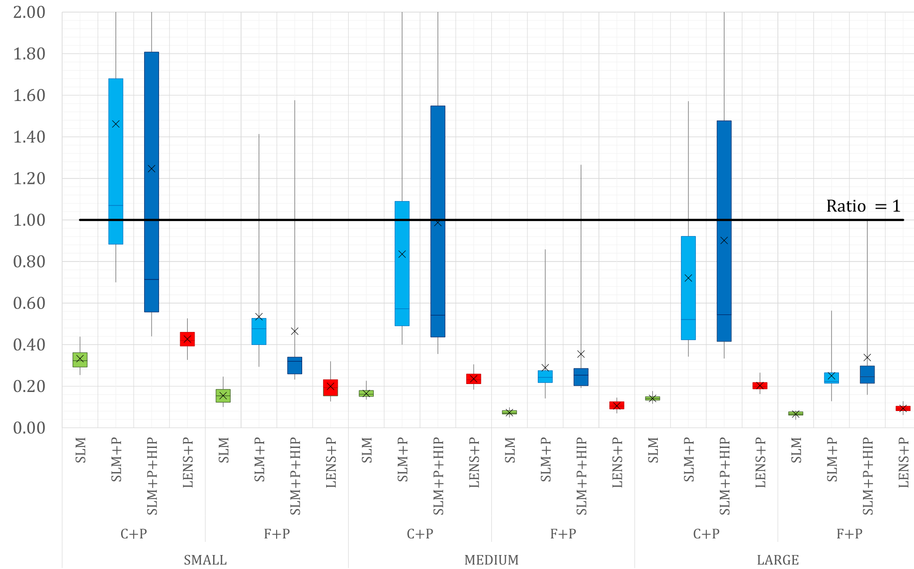

Fig. 7. Box-and-whisker plot of threshold AM production cost.

also be considerable. In very few cases, when whiskers are closed to the horizontal red line, these AM options could be considered suitable alternatives. When the part is complex and the most suitable CM option is the C + P, the SLM + P and SLM + P + HIP options are the best solution, especially when the parts are small. When the spare parts are medium or large, the ratio is lower than 1 but still in many scenarios it has values that the advancements in the AM technologies could contribute to achieve.

4.4. Decision trees

Finally, a decision tree is presented to answer the last research question, and it provides a guideline for practitioners to understand under which conditions the AM options are economically profitable. A decision tree (Bishop 2006) is a supervised classification technique used to predict—given a set of attributes—to which class an item belongs. In our case, a decision tree identifies the best option (i.e., class) given a set of attributes related to the spare parts applications and AM/CM options (i.e., *Size*, c_b, $MTTF_{cast}$, T_i, L_i).

Separate decision trees are trained to identify the best options based on the complexity of the spare parts. As CM options, F + P and C + P are considered for simple and complex parts, respectively. For AM options, only SLM + P and SLM + P + HIP are considered both for simple and complex parts as being the cheapest options.

Multiple scenarios are analysed, training two decision trees, one for simple and one for complex parts:

Scenario A) Considering all the data for the MTTF ratio.
Scenario B) Considering the data for the MTTF ratio published over the last three years.
Scenario C) Considering limited inventory capacity $S_{max} = 0$ or $S_{max} = 1$ and the last three years of published data.

The comparison between the entire data set and the recent 3 years data set identifies under which circumstances AM technological advancements are effective. The comparison between unlimited and limited inventory capacities identifies the advantages of readily available AM items against their CM counterparts.

The dataset used results from an extended analysis of 1188 attribute combinations (i.e., items) obtained according to Table 7 with the constraint $T_i \geq L_i$.

The choice of decision trees over logistic regressions is because of the ease of interpretation of the obtained results. Moreover, the purpose of our parametric analysis is limited to data description (e.g., Lolli et al., 2019), and it should not be used for class prediction; indeed, such an objective would require partitioning the data into two sets to separately train and validate the trees. Conversely, here, the decision trees are fed with all the data at once to extrapolate some meaningful insights.

Table 7
Attribute values combined to achieve the inputs for the decision trees.

Attribute	Range
size	small, medium, large
$MTTF_{cast}$	26, 52, 78, 104, 130, 156
c_b	1000, 6000, 11000, 16000, 21000, 26000, 31000, 36000, 41000, 46000, 51000
T_i	4, 8, 12
L_i	4, 8, 12

The tree is created by having the 1188 items flow from the root. At each node, including the root, two separate branches are generated using the Gini diversity index (*gdi*) (Margolin and Light 1974) as a splitting criterion:

$$gdi = 1 - \sum_{i=1}^{3} p(i)^2 \tag{8}$$

where 3 is the number of options (e.g., C + P, SLM + P and SLM + P + HIP for complex parts) and $p(i)$ is the number of items reaching the node and having i as their best option over the total number of items reaching the node.

At each node j, an attribute and its cut point are chosen to generate the two branches, with the aim to minimise:

$$\frac{m_{left}}{m} gdi_{left} + \frac{m_{right}}{m} gdi_{right} \tag{9}$$

where m is the number of items in the original node; m_{left} is the number of items in the new node on the left branch; m_{right} is the number of items in the new node on the right branch; gdi_{left} is the Gini diversity index in the new node on left branch; and gdi_{right} is the Gini diversity index in the new node on the right branch. The items are sorted into the two branches according to the value of their attribute compared with the cut point.

The performance of the tree is evaluated by either the error rate, which is the number of misclassified items over the total number of items, or accuracy a, which is the opposite. Because each tree can reach up to 100% accuracy, a pruning technique can be applied to make it more readable. Pruning deletes nodes, starting from the lowest ones and decreasing the tree complexity at the cost of decreasing its accuracy. If pruning leads to a much lower accuracy, it can be concluded that the effects of the attributes on the best class are strongly mixed, and the decision tree loses its ability to facilitate data interpretation. To make the decision trees effective in representing the data, we force the pruning to reach three-level-deep trees (i.e., three splitting levels).

Each leaf of the achieved trees is evaluated in terms of the following:

- p: the percentage of items reaching the leaf.
- a: the accuracy.
- c: the average percentage of the increased cost when the wrong option is selected.

Interested readers can refer to Bishop (2006) for a more in-depth explanation of decision trees.

4.4.1. Scenario A) considering all the data for the MTTF ratio

When the parts are simple, F + P is always preferred to AM. In this context, a decision tree is not required.

In the case of complex parts, that is, when C + P is the CM, the comparison between C + P and AM (SLM + P/SLM + P + HIP) leads to a nine-level-deep decision tree. This tree can be pruned to obtain a three-level-deep decision tree with 96.6% accuracy, which translates to an average of a 4.2% increased cost when the wrong option is selected.

The most important features are c_b, $MTTF_{cast}$ and *size*, but their order and amount vary depending on the tree branch. It can either be $c_b \succ MTTF_{cast}$ or $c_b \succ size \succ MTTF_{cast}$.

The decision tree can be reshaped, obtaining a more symmetric structure (Fig. 8) without changing the classification results.

The only differences between the two branches are as follows:

- If $c_b < 3500$ (left branch), the feature *size* is not discriminant, and $MTTF_{cast}$ leads either to C + P or to SLM + P + HIP, while if $c_b \geq 3500$ (right branch), the *size* is the feature leading either to C + P or SLM + P.
- The $MTTF_{cast}$ cut points are different, and their effects are reversed. If $c_b < 3500$ and $MTTF_{cast} \geq 65$, then SLM + P + HIP is optimal, while if $c_b \geq 3500$ and $MTTF_{cast} \geq 39$, C + P is optimal.

The cut point for c_b is between 1000 and 6000, the two lowest values for c_b in the dataset. The right $c_b \geq 3500$ branch can be considered the baseline, and only very small values of c_b can impact the optimal option.

The cut points for the $MTTF_{cast}$ differ depending on the branch; they are between 52 and 78 and between 26 and 52 for the left and right branches, respectively.

Fig. 8 reports the performance *p, a, c* of the leaves of the pruned and reshaped tree. The most robust option selection is C + P for parts with $c_b \geq 3500$, where 75.8% and 10% of the items are classified with a 97.4% (for $MTTF_{cast} \geq 39$) and 100% (for $MTTF_{cast} < 39$ and $size = \{medium, large\}$) accuracy, respectively.

4.4.2. Scenario B) considering the data for the MTTF ratio published over the last three years

When the parts are simple, F + P is preferred for 1174 items over 1188. In this context, to properly classify the remaining 14 items into the classes SLM + P and SLM + P + HIP and, thus, to reach a 100% accuracy, the decision tree identifying the attributes for which AM is preferred would be very deep and data dependent but with the effect of losing its readability. The only robust result is that F + P is dominant over AM, with an average of a 15.1% of increased cost for the 14 incorrectly classified items.

For more complex parts or in case C + P is the CM option used, a nine-level-deep decision tree is obtained. This tree can be pruned to obtain the three-level-deep decision tree with 96% accuracy, which is depicted in Fig. 9 and which translates to an average 3.7% increased cost when the wrong option is selected. Fig. 9 reports the performance of *p, a, c*.

The most important features of the pruned tree are, in order $c_b \succ size \succ MTTF_{cast}$. The decision tree structure is similar to the one in Fig. 8, except that the root $c_b < 3500$ branch leads only to SLM + P + HIP. In fact, the effect of the improvement in material properties of AM technologies and post-process treatments is to make the SLM + P + HIP the optimal solution when $c_b < 3500$. C + P is again the most robust option selection for medium and large parts with $c_b \geq 3500$, where 60.6% of items are classified with a 100% accuracy.

4.4.3. Scenario C) considering limited inventory capacity $S_{max} = 0$ or $S_{max} = 1$ and the most recent three years of published data

In all the $S_{max} = 0$ cases, SLM + P + HIP is preferable 100% of the time both for simple and complex parts. Therefore, no decision tree is required to interpret such results.

In the case $S_{max} = 1$ and of simple parts (i.e., F + P is compared with SLM + P and SLM + P + HIP), SLM + P and SLM + P + HIP are dominant over F + P and are preferred 53.9% and 22.3% of the times, respectively. A 12-level-deep decision tree is obtained, but in this case, pruning is quite ineffective and results in a two-level-deep decision tree with 75.3% accuracy, which is depicted in Fig. 10 and which translates to an average 58.7% increased cost when the wrong option is selected. Indeed, the limited number of cases where F + P is preferred is hard to model, generating a low accuracy in the pruned tree. The 12-level-deep decision tree with 100% accuracy would be too deep to represent the data and extremely case sensitive as well, hence losing its readability. To increase the accuracy of the pruned tree, a tree deeper than two levels could be achieved. However, pruning makes the pruned trees pass directly from the five-level-deep to the two-level-deep tree without allowing for three-level-deep and four-level-deep trees; yet the five-level-deep tree is still ineffective in representing the data and providing a low accuracy (82.9%).

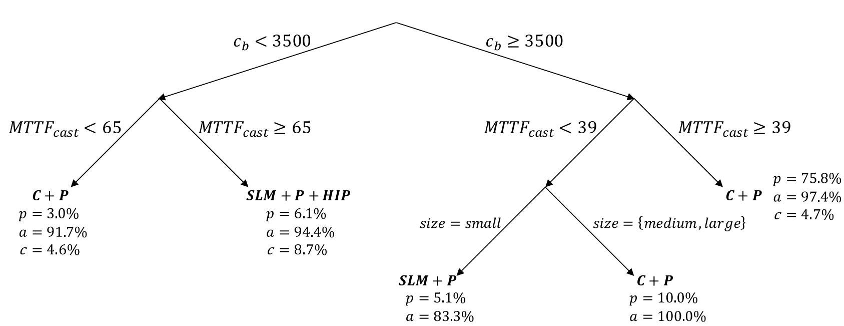

Fig. 8. *Scenario A for complex parts: Option selection and p, a, c of leaves.*

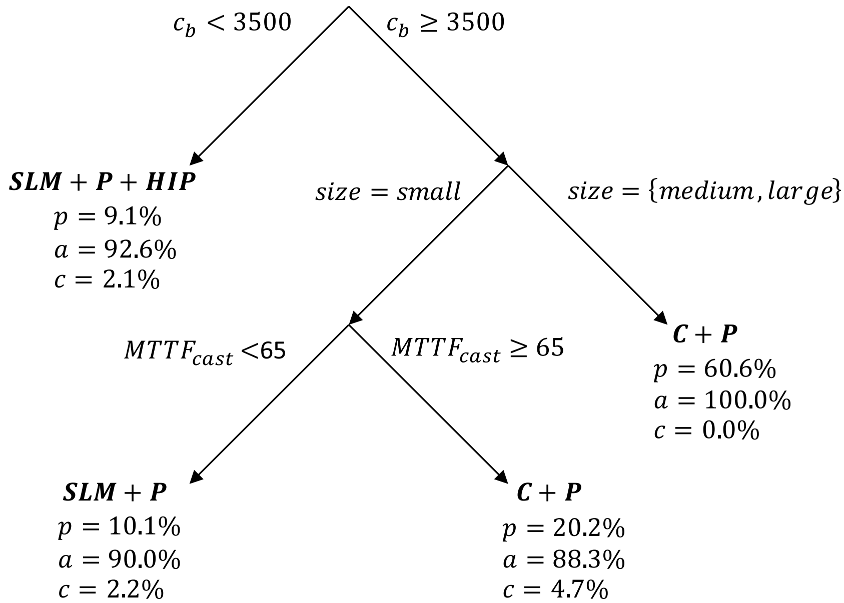

Fig. 9. Scenario B for complex parts: Option selection and p, a, c of leaves.

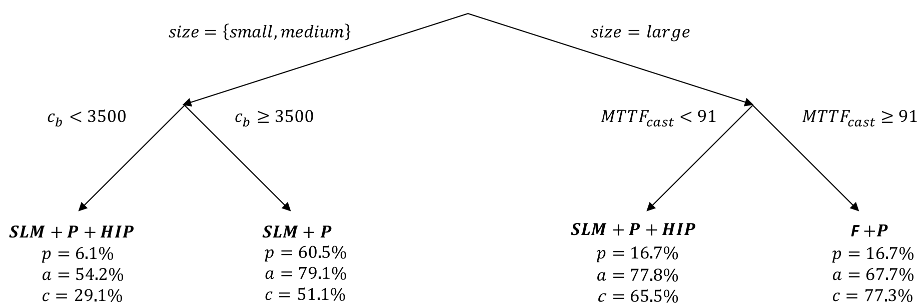

Fig. 10. *Scenario C for simple parts and* $S_{max} = 1$*: Option selection and* p, a, c *of leaves.*

The most important feature is *size*, and the two branches are different; for parts with a small and medium *size*, c_b discriminates between SLM + P and SLM + P + HIP, while for large parts, $MTTF_{cast}$ splits the items into F + P and SLM + P + HIP classes.

In Fig. 10, most of the increased costs is because of the F + P class for large parts and $MTTF_{cast} \geq 91$.

In the case where $S_{max} = 1$ and there are complex parts (i.e., C + P is compared with SLM + P and SLM + P + HIP), AM always outperforms CM, where SLM + P and SLP + P + HIP are preferred 64.1% and 35.9% of the times, respectively. An eight-level-deep tree is obtained, and pruning allows for reaching the three-level-deep tree depicted in Fig. 11, here with a 90.4% accuracy translating to an average 11.8% increased cost when the wrong option is selected. The right branch is equal to the right branch of Fig. 10, where parts of a small and medium *size* are split by c_b between SLM + P and SLM + P + HIP. Conversely, the left branch shows three levels, where AM is always preferred for large parts and the choice between SLM + P and SLM + P + HIP depends on $MTTF_{cast}$ and c_b. In Fig. 11, high accuracy values are identified for all the leaves. However, the SLM + P class for parts with a small and medium *size* and $c_b \geq 3500$, which is the largest class, is also the least accurate, thus worsening the overall performance of the tree.

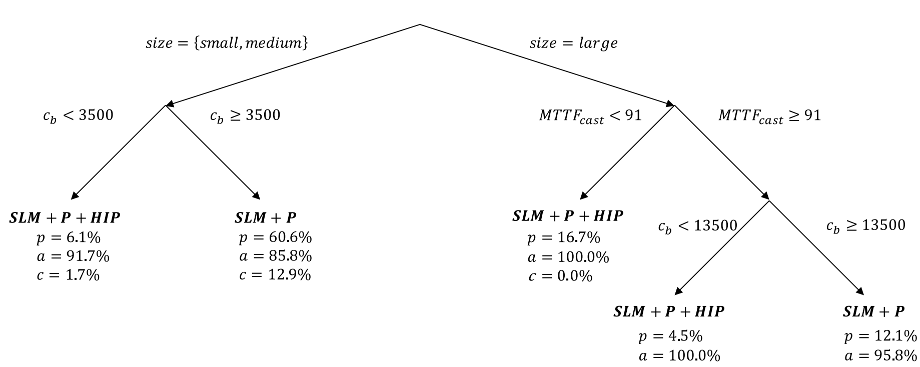

Fig. 11. Scenario C for complex parts and $S_{max} = 1$: Option selection and p, a, c of leaves.

5. Conclusions and further research agenda

Our paper proposes a periodic review inventory management system for spare parts to establish the most economically profitable option among CM and AM technologies when coupled with post-process treatments. An extensive parametric analysis was performed on a 316L stainless steel parts characterised by three different sizes to evaluate how mechanical properties and economic and technological parameters affect the best option, thus make the transition from CM to AM more or less attractive. In particular, the mechanical properties are expressed in terms of MTTF, which is provided by accelerated tests, representing nowadays the only viable alternative to testing parts at their usage conditions in order to achieve the said reliability data for parts produced via AM.

The following list summarises our main findings:

- The profitability of AM generally increases for small parts, low backorder costs, high procurement lead times of the counterpart produced via CM and high review periods.
- If the storage space is unbounded and, thus, the order-up-to level has no upper bounds, F + P is always the best option for simple parts. However, when considering the last three years of MTTF ratios, AM increases its profitability because of the improved mechanical properties of parts produced via AM, to such an extent that SLM + P with/without HIP outperforms F + P for small parts, low backorder costs, high MTTF and procurement lead times of the counterpart produced via CM, and high review periods. Conversely, SLM + P with/without HIP is always the best option for complex parts and low backorder costs. If the backorder costs increase, the profitability of SLM + P with/without HIP increases by lowering the MTTF of the counterpart produced via CM and increasing its procurement lead times and the review periods.
- If the storage space is null, for example, in remote facilities such as offshore platforms, all the AM options are better than CM options. However, if one part might be in stock, the observed trends for simple and complex parts are quite different.

For simple parts, F + P is always cheaper than SLM and LENS + P, while the comparison with SLM + P and SLM + P + HIP depends on the spare part application and AM/CM features. In particular, the SLM + P + HIP option is always the cheapest AM solution for small parts because of the low unitary production costs. Increasing the part size, F + P becomes the best option for high review periods.

For complex parts, in the case of the lowest backorder costs, the AM options outperform the CM options for small parts, where SLM + P + HIP represents the best option, save for in cases with low procurement lead times and review periods. However, when the part size increases, SLM and LENS + P lose their profitability compared with C + P because of a reduction in both the procurement lead times of the counterpart produced via CM and the review periods.

Given the evolving and wide range of AM options, it follows that the transition from CM to AM is a complex issue to address. Nevertheless, under our inventory management system, some meaningful insights can be deduced:

- SLM and LENS + P should lower the production costs by around 60–90% to become competitive with CM, but this is an unlikely scenario in the near future.
- SLM + P and SLM + P + HIP are still too expensive for simple parts. However, for complex and small parts, they often represent the best options. When the part size increases, they lose their profitability, but further improvements on their mechanical properties and production costs could change this scenario in the near future.

It is worth noting that the achieved results are strictly related to the inventory management system. In particular, we adopted a Poisson demand-generating process, which can be set by means of the predicted MTTF as being a mono-parameter function. If we had used the common three parameters in the Weibull function, the accelerated tests would not have been enough for the parts produced via AM. Thus, our further research agenda will focus on the adoption of other probability density functions and inventory management systems. Moreover, alternative preventive maintenance strategies will also be considered, as well as multicriteria inventory classification approaches to drive practitioners towards the most rational choice of the sourcing options based on their specific scenarios. Finally, our future researches will also focus on overcoming the main limitations of this paper:

- *Investigated materials:* different class of materials (metallic materials, polymers, composites) and different materials (Titanium alloys, Aluminium alloys, …) need to be also considered to have a better overview of the impact of AM on the spare parts inventory management;
- *Model assumptions:* multi-item approaches, limited AM equipment capacity should also be considered; moreover the geometrical complexity should be included in a more explicit way in the inventory model, such as different design costs between AM and CM parts, different order costs and possible re-design of AM parts.

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