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Choosing between additive and conventional manufacturing of spare parts: On the impact of failure rate uncertainties and the tools to reduce them

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ABSTRACT

Recently, there has been great interest in using additive manufacturing (AM) to produce spare parts: allowing to produce spare parts with short lead times and close to the point of use, AM reduces the need for large inventories otherwise required by conventional manufacturing (CM) techniques to deal with intermittent spare parts demand. However, using AM to produce spare parts is limited by two main drawbacks: high production costs and uncertain failure rates arising from AM still being a relatively new production technique. While the former can be counterbalanced by inventory cost reductions, it is unclear how the latter impacts the sourcing option decision (i.e. AM or CM). We aim to fill this gap by studying a periodic review model in which spare parts demands follow a Poisson process. To make our analysis accurate and reliable, we leverage a material science approach to obtain realistic values for the failure rate uncertainties. From the results, it emerges that AM is heavily penalized by failure rate uncertainties much higher than those of CM. Consequently, we then focus on some recent tools developed to reduce AM failure rate uncertainties: porosity assessment and in-situ monitoring. We find that the failure rate uncertainty should be reduced by five and six percentage points to make it worthwhile to invest in porosity assessment and in-situ monitoring, respectively. Finally, we determine under which circumstances each tool is preferred over the other and found that porosity assessment is typically the most competitive uncertainty reduction tool.

1. Introduction

Correct spare parts management is now widely recognized as a crucial task to ensure high availability of manufacturing systems. However, the intrinsic characteristics of spare parts (e.g. significant supplier dependency, long procurement lead times, high downtime costs when spare parts are missing, and intermittent demands that are difficult to predict in terms of both quantity and frequency) render this task complex and require spare parts managers to adopt high inventory levels to counterbalance resulting risks (Huiskonen, 2001).

Additive manufacturing (AM) has recently drawn the attention of researchers and practitioners as a potential breakthrough in the world of spare parts. Indeed, by enabling the production of spare parts close to the point of use and with reduced lead times, AM allows to decrease the high inventory levels necessary when producing spare parts with conventional manufacturing (CM) techniques (e.g. machining, casting, and forging) (Walter et al., 2004; Peron, 2024).

In the light of these benefits, the AM market for spare parts and Maintenance, Repair, and Overhaul (MRO) services has witnessed a significant growth, accounting now for circa 50% of the total AM market (Meticulous Research, 2024), which was worth \$16.14 billion in 2023 and is expected to exceed \$40 billion by 2028 (Research and Markets, 2024). However, the use of AM for spare parts manufacturing could further increase, but it is accompanied by two major drawbacks: high production costs and uncertain failure rates. As for the former, researchers and practitioners have begun assessing whether or not the

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decrease in inventory level (and hence inventory costs) can offset such high production costs (Westerweel et al., 2018; Knofius et al., 2020; Sgarbossa et al., 2021; Peron et al., 2024), showing how this could be possible in certain situations (cf. Section 2 for more details).

Concerning the second main drawback of AM, i.e. its highly uncertain failure rates,[1] this arises from the intrinsic nature of the AM manufacturing process where even small changes in the toolpath and in the surrounding conditions can lead to big deviations in the failure rate of the resulting part (Peron et al., 2022). Based on this and on the fact that AM is a manufacturing technique that is still undergoing significant industrial technological advancements (Stavropoulos et al., 2018) (contrarily to CM), the failure rate uncertainty of AM parts is larger than for CM counterparts. Researchers are well aware of this. Indeed, Westerweel et al. (2018) stated that *"a current limitation of AM technology is that there is often uncertainty concerning the mechanical properties of such parts"*, and similarly Knofius et al. (2020) reported that, together with high unit costs, *"uncertain reliabilities of printed parts often rule out the use of AM"*. In fact, as shown by Van Wingerden et al. (2017) for CM parts, the higher the failure rate uncertainty, the higher the inventory costs (this is further proved mathematically in Appendix B); given the fact that AM has its highest benefits in terms of inventory costs reduction, it is clear that failure rate uncertainties can be expected to affect the convenience of AM for spare parts production. In addition to this, one has to consider that AM parts might be used in safety-critical applications (i.e. in applications where the failure of such part will have safety concerns). Here parts (no matter the production technology), before being used in such applications, have to undergo extensive quality control procedures to ensure that they will meet certain minimum requirements in terms of, among others, failure rates (Peron et al., 2023; DNV, 2022). Intuitively, parts characterized by higher failure rate uncertainties are more likely to fail to meet such minimum requirements than parts characterized by lower failure rate uncertainties. This, however, would lead to additional costs: parts failing to meet the minimum requirement, in fact, cannot be used and they need to be discarded, produced again (hence incurring in additional production costs) and tested again for quality (hence incurring again cost associated with expensive and time-consuming quality control procedures). Being AM characterized by failure rate uncertainties higher than CM, these additional costs would thus further affect the competitiveness of AM for spare parts production.

Nevertheless, despite all the above considerations, to the best of the authors' knowledge, there are no extensive works investigating the impact of failure rate uncertainties on the competitiveness of AM for spare parts production and consequently on the choice about the preferable sourcing option (cf. Section 2 for more details). In this work, we aim to fill this gap, carrying out a thorough investigation of how failure rate uncertainties impact the sourcing option decision (i.e. whether to manufacture spare parts in AM or CM). More in detail, in doing so, this work focuses only on parts used for non-safety-critical applications (i.e. applications where the failure of such part will not have safety concerns). This choice is driven by the fact that currently AM is mostly used for producing spare parts for such applications (Jæger et al., 2023; Mally et al., 2022; Bikas et al., 2016). As an example, when discussing the use of AM in automotive, DesignSolutions (2019) stated that *"3D printing is certainly present in vehicle manufacturing. However, it is not suitable for production of safety critical parts"*. Similarly, Mally et al. (2022) reported that AM is mainly used for *"non-safety-critical small to medium-sized components"*. Consequently, as described above, to investigate the impact of failure rate uncertainties on the sourcing option decision (AM/CM), the focus should be on inventory management and its related costs. Therefore, the research question (RQ) we aim to answer is the following.

RQ1. From an inventory management perspective, how do the failure rate uncertainties impact the sourcing option decision (AM/CM)?

To do so, we have considered two situations, a benchmark situation where the failure rate uncertainties of AM and CM parts are neglected (i.e. the failure rates of AM and CM are assumed to be known precisely) and a situation where instead the failure rate uncertainties are considered. Per each situation, considering as inventory management model a periodic review model in which spare parts demands follow a Poisson distribution as often done in the literature (Babai et al., 2011; Sgarbossa et al., 2021), we have identified when AM is the preferable sourcing option and when not. In this way, we were able to identify AM/CM convenience areas (in terms of backorder costs, production costs, lead times, …) for the two situations, and then, through their comparison, it was hence possible to determine how failure rate uncertainties impact the sourcing option decision and the AM/CM convenience areas. Notice that to render the analysis accurate and reliable, we have leveraged a material science approach to determine realistic values of the failure rate uncertainties. By doing so, we have observed that AM is heavily penalized by its higher failure rate uncertainties, with the convenience of AM decreasing from almost 76%–45.1% of the scenarios analyzed.

In the light of these results and considering the recent advancements made by researchers in the material science field to reduce the failure rate uncertainties of AM, we have further extended this work considering a future scenario. Indeed, new technologies such as porosity assessment and in-situ monitoring coupled with previously-built databases can be used to reduce the failure rate uncertainties of AM (Wang et al., 2020). In this future scenario we elaborate on their use: if on the one hand their adoption will be beneficial for AM leading to inventory management-related savings, on the other hand it has to be considered that they come at an additional cost, hence further increasing the AM-related production costs. Thus, in this work, for the first time in the literature, we try to understand whether their use might be beneficial for AM or not, answering the following RQ.

RQ2. Considering the tools to reduce AM failure rate uncertainties, what is the failure rate uncertainties reduction that each tool should achieve to justify the additional costs?

To do so, first we have identified the three main tools to reduce the failure rate uncertainties of AM (i.e. porosity assessment, in-situ monitoring, and sacrificial testing) and the associated costs through a discussion with experts in the sector. Then, through a comparison with the results previously obtained for the situation where the failure rate uncertainties are considered, we have determined how much each of these tools should bring in terms of reduced AM failure rate uncertainties to justify the additional costs. By doing so, we have observed that sacrificial testing is characterized by additional costs that are too high, with its adoption that cannot hence be justified by the benefits achievable by the reduced AM failure rate uncertainties. On the contrary, the adoption of porosity assessment and in-situ monitoring can instead be justified if porosity assessment is able to decrease AM failure rate uncertainties from its current value (48%) to at least 43% and if in-situ monitoring is able to decrease it to at least 42%. Finally, we have determined when each tool is to be preferred over the other. More in detail, we have observed that overall porosity assessment is to be preferred. Thanks to these results, practitioners and researchers in the field are now supported in understanding whether the adoption of such tools is justifiable or not (and which one should eventually be used) and in carrying out

[1] Parts in machines fail randomly. For a group of machines, the resulting demand process for spare parts then often follows a Poisson process with a certain failure rate, λ (Babai et al., 2011). However, the expected value of the failure rate λ is not known precisely in practice, but it is characterized by a certain uncertainty. This uncertainty can derive from the application of the part (when parts are used in new machines or when such machines are used under different circumstances, the expected value of the failure rate is definitely not known precisely) and/or be an intrinsic characteristic of the manufacturing technology adopted, which is the case under consideration in this work. Following Van Wingerden et al. (2017), we refer to such uncertainty in the expected value of the failure rate λ as "failure rate uncertainty".

R&D activities to achieve the required AM failure rate uncertainties. We elaborate better on the implications of this work in the Conclusion (Section 5). These are preceded by a summary of the literature on the use of AM in spare parts inventory management (Section 2), the description of the methodology adopted (Section 3), and the presentation and discussion of the results (Section 4).

2. Literature review and contribution

In Section 2.1, we first elaborate on the current literature on the main topic of this work, i.e. whether to use AM or CM for producing spare parts. This allows to identify the main contribution of this work, which is described in detail in Section 2.2.

2.1. Literature review

As described above, the reduced lead times of AM compared to the long ones of CM have increased the interest towards AM, suggesting a transition from CM to AM for producing spare parts. The profitability of such transition, however, is not straightforward since AM and CM parts are characterized by different characteristics, e.g., higher production costs and higher failure rate uncertainties. As described above, when dealing with parts used for non-safety-critical applications, the transition in question must be assessed based on the costs associated with the inventory management system adopted. However, there is limited literature addressing the sourcing options decision (AM/CM) within the spare parts management domain, and the following provides a concise summary of these contributions (for a more extended overview please refer to Table A1 in Appendix A).

Following Holmström et al. (2010) who called for quantitative research on the use of AM for spare parts, Khajavi et al. (2014) evaluated the costs of adopting AM in the spare parts supply chain of the F-18 Super Hornet fighter jet considering current and future scenarios in terms of AM costs. This represented one of the first quantitative work on the subject, shedding lights on the AM-related costs, but it did not provide a comparison with CM. This was done instead by Liu et al. (2014), who again focused on aircraft spare parts supply chains, comparing AM and CM as sourcing option. However, despite being the first work to quantitatively compare the two sourcing options, Liu et al. (2014) compared AM and CM only in terms of inventory levels (showing that AM would reduce them up to 70% compared to CM), neglecting relevant cost items such as production/purchasing costs. Similar studies focusing only on inventory levels and costs are those of Sirichakwal and Conner (2016) and Ghadge et al. (2018).

The importance of considering production/purchasing costs was confirmed by Li et al. (2016). Li et al. (2016) considered all cost items and they confirmed the literature results related to the convenience of AM as sourcing option if inventory costs are the only costs to be considered. However, they also showed that when the production/purchasing costs are considered, AM is no longer the preferable sourcing option, but CM should be adopted. The impact of production/purchasing costs was then better investigated by Khajavi et al. (2018), Knofius et al. (2019), Heinen et al. (2019), Zhang et al. (2019), Rinaldi et al. (2021), and Mecheter et al. (2024). As an example, Khajavi et al. (2018) developed a model to investigate the impact of different AM production costs (resulting from different AM machines and/or raw materials) on the production switchover quantity for AM – CM. Similarly, also Knofius et al. (2019) developed a mathematical model to support the identification of AM areas of convenience, showing that AM is convenient when backorder costs are high, the difference between AM and CM lead times is high, and when the difference between AM and CM production/purchasing costs is low. Moreover, they also showed that considering the commonly high AM production/purchasing costs, a dual sourcing option where CM is used for regular supply and AM is used for emergency supply is the best option. This was further shown by Song and Zhang (2020), Knofius et al. (2020), and Roozkhosh et al. (2024), who showed that the dual sourcing option is always preferable to the single sourcing one (either AM or CM), with cost savings of more than 40% compared to the best single sourcing approach even if AM production/purchasing costs or AM failure rates were three times higher than those of CM counterparts.

Interestingly, Knofius et al.'s (2020) work, together with that of Westerweel et al. (2018, 2021), was one of the first to consider that AM failure rates differ from CM ones. More in detail, considering the poor technological developments of the first AM machines, these contributions considered AM failure rates to be higher than the CM ones. This, however, is not always the case since state-of-the-art AM machines coupled with post-process operations can lead to AM parts with failure rates lower than CM counterparts. This was investigated for the first time by Sgarbossa et al. (2021). Indeed, in the development of a machine learning-based decision support system to identify the suitable sourcing option, Sgarbossa et al. (2021) were pioneers in adopting a multidisciplinary approach to determine the actual failure rate of AM and CM considering different AM and CM technologies and post-processing operations. Following this work, some other papers followed such a multidisciplinary approach to determine the failure rates of AM and CM (Cantini et al., 2024; Peron et al., 2024). However, these works did not consider the uncertainties of the failure rates (both for AM and CM), and how these impact the sourcing option decision. Indeed, despite Van Wingerden et al. (2017) showed for CM parts that inventory costs increase with an increase in the failure rate uncertainty, to the best of our knowledge it has not been investigated how the failure rate uncertainties impact the sourcing option decisions. Indeed, in the literature only one work on the topic can be found (Peron et al., 2022), which is however, as defined by the authors themselves, *"a preliminary study"*, and hence with limited insights given the limited test bed made up of few scenarios. This work, hence, aims to fill this gap, providing a thorough investigation of how the failure rate uncertainties impact the sourcing option decisions considering both current and future scenarios. We further elaborate on the contribution of this work in the next section.

2.2. Paper contribution

As highlighted in the previous section, when trying to shed lights on whether spare parts should be produced in AM or CM, most of the literature fails to consider the recent technological advancements for AM spare parts production. These, indeed, have made so that state-of-the-art AM machines coupled with post-process operations can lead to the production of AM parts with failure rates that are lower than CM counterparts. This work moves away from most of the literature and considers that AM parts are characterized by lower failure rates than CM counterparts. This represents already a preliminary contribution.

The main contribution, however, is represented by the fact that this work considers that both AM and CM failure rates are uncertain, with the failure rate uncertainty of AM parts being larger than that of CM counterparts. As discussed above, there is only one work (Peron et al., 2022) investigating how the failure rate uncertainties of AM and CM parts affect the sourcing option decision. Such work itself was defined by the authors as a *"a preliminary study"* given the limited number of scenarios considered. In this work, hence, we extend such work, carrying out a thorough investigation of how failure rate uncertainties affect the spare parts sourcing option decision (i.e. AM/CM). This represents the second contribution of this work.

Finally, this work further contributes to the literature elaborating for the first time on the tools to reduce AM failure rate uncertainties. Specifically, this work provides for the first time an understanding of how much each of these tools should bring in terms of reduced AM failure rate uncertainties to justify the additional costs.

In conclusion, to summarize, the contribution of this work to the literature investigating whether spare parts should be produced in AM or CM are the follows.

1. This work considers the technological advancements for AM spare parts production considering that AM spare parts are characterized by lower failure rates than CM counterparts (minor contribution);
2. This work considers that both AM and CM failure rates are characterized by a certain uncertainty, with AM failure rates uncertainties being higher than CM ones, and investigates in an extensive way how this impact the sourcing option decision (major contribution, first time in the literature);
3. This work considers that tools to reduce AM failure rate uncertainties can be introduced, and it investigates whether these should be adopted or not given their performance in terms of AM failure rate uncertainties reduction (major contribution, first time in the literature).

3. Methodology

In the following we will describe the methodology adopted in this work (which is schematically represented in Fig. 1). Specifically, Section 3.1. reports the mathematical models used to determine the inventory management costs in case of failure rate uncertainties considered or not considered (i.e. benchmark situation). Section 3.2., then, describes the procedure used to develop the two aforementioned decision trees. The material science approach used to determine the realistic values of the failure rate uncertainties of AM and CM parts is discussed in Section 3.3. Finally, Section 3.4 reports the methodology adopted for the analysis of the future scenario where new tools for reducing AM failure rates uncertainties are considered to be adopted. Notably, this work has been developed considering metallic spare parts (specifically stainless steel) produced in SLM. The choice to focus on stainless steel as material and SLM as AM process derives from the fact that the majority of spare parts are made out of this material and that SLM is one of mostly used AM process to produce stainless steel parts. However, the methodology adopted is valid for other materials and AM processes.

3.1. Mathematical model

As described above, the mathematical models used to calculate the spare parts management costs for (i) the benchmark situation where AM and CM failure rates are assumed to be known precisely, i.e. without any uncertainty, and for (ii) the situation where instead failure rates are not known precisely but with a certain uncertainty (as it is in real life) will be presented in this section.

Dealing with the benchmark situation, we have adopted the periodic review model with Poisson distributed demand used by Sgarbossa et al. (2021) to determine the total spare parts inventory management costs C_{tot}. These are defined in Equation (1), and they are the sum of the holding costs (C_h), backorder costs (C_b) and purchasing costs (C_p), which are defined in Equations (2)–(4), respectively. These costs depend on the sourcing option x, where x can be AM or CM. Therefore, from now on all the parameters and variables depending on the sourcing option will have superscript x.

$$C_{tot}^x = C_h^x + C_b^x + C_p^x \tag{1}$$

$$C_h^x = h \bullet c_p^x \bullet \sum_{y=0}^{S^x-1} (S^x - y) \bullet P_{\lambda^x, T^x+L^x, y} \tag{2}$$

$$C_b^x = c_b \bullet \sum_{y=S^x+1}^{\infty} (y - S^x) \bullet P_{\lambda^x, T^x+L^x, y} \tag{3}$$

$$C_p^x = \lambda^x \bullet c_p^x \tag{4}$$

Where h is the holding cost rate, c_p^x and c_b are the unitary purchasing and backorder costs, respectively, y is the realization of the stochastic demand (i.e., the number of realized failures in the period $T^x + L^x$), L^x is the lead time, T^x is the review period, λ^x is the failure rate and $P_{\lambda^x, T^x+L^x, y}$ is the probability of having y failures over the period $T^x + L^x$ given the failure rate λ^x. Then, S^x is the order-up-to-level. In the remainder of this paper, the order-up-to-level minimizing the total costs will be used, and we denote that optimal inventory level by S^{x^*}. Following the literature and practice, AM and CM are considered to be characterized by different unitary purchasing costs c_p^x and by different failure rates λ^x. More in detail, as it will be better described below, following Knofius et al. (2020), the unitary purchasing costs of AM are considered higher than those of CM; in the following we will use the parameter r_p to express the ratio between AM and CM unitary purchasing costs, and the unitary purchasing costs of CM parts will be considered as reference value. Then, following Sgarbossa et al. (2021), the failure rate of AM parts is considered 5.2 times lower than that of CM parts. In the following, the failure rates of CM parts will be considered as reference values.

Dealing now with the situation where the exact values of the failure rates of AM and CM are characterized by a certain uncertainty, we follow Van Wingerden et al. (2017) to determine the total spare parts management costs C_{tot}^x. The expectation of the failure rate is still described with λ^x, but its exact value follows a truncated normal distribution N^x (truncated such that $N^x \geq 0$), with standard deviation σ^x and probability density function f_n^x. Based on this, the holding costs C_h^x, backorder costs C_b^x and purchasing costs C_p^x are now modified according to Equations (5)–(7), respectively.

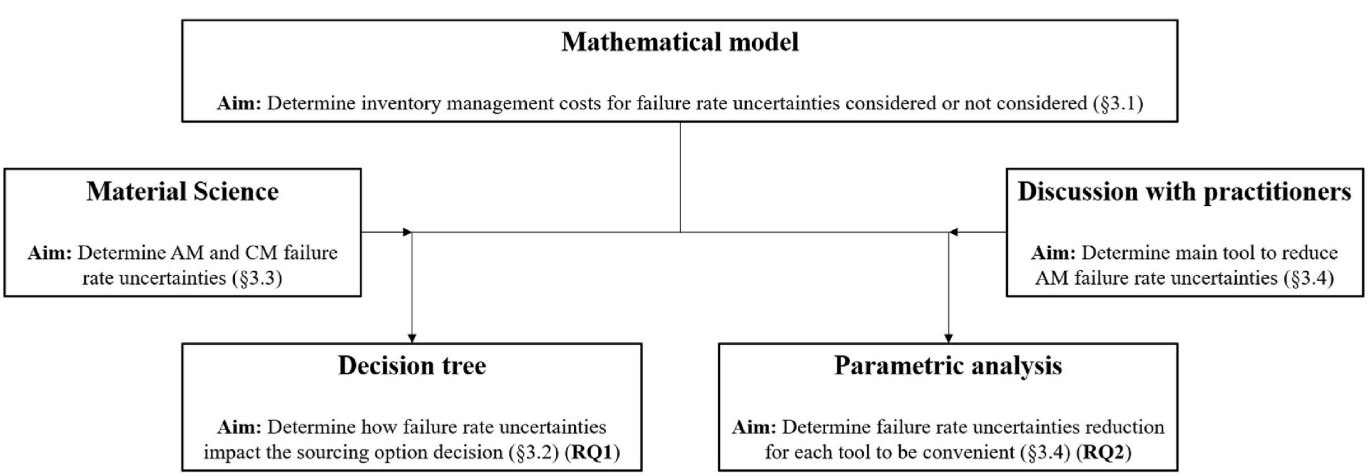

Fig. 1. Schematic representation of the methodology adopted and its link with the RQs.

$$C_h^x = h \bullet c_p^x \bullet \int_0^\infty f_n^x(z^x) \bullet \sum_{y=0}^{S^x-1} (S^x - y) \bullet P_{z^x, T^x+L^x, y} dz^x \tag{5}$$

$$C_b^x = c_b \bullet \int_0^\infty f_n^x(z^x) \bullet \sum_{y=S^x+1}^{\infty} (y - S^x) \bullet P_{z^x, T^x+L^x, y} \, dz^x \tag{6}$$

$$C_p^x = c_p^x \bullet \int_0^\infty f_n^x(z^x) \bullet z^x dz^x \tag{7}$$

where z^x is the realization of the normal distribution N^x.

The mathematical proof that the higher the failure rate uncertainty the higher the spare parts management costs for the inventory management model considered can be found in Appendix B.

3.2. Decision tree

A decision tree is a graphic tool suitable for supporting the decision-making process and easily identifying areas of convenience: given a set of attributes (in our case the spare parts demand, backorder costs, purchasing costs, lead time, …), it suggests the optimal solution (in our case the optimal sourcing option). In other words, it supports an easy and intuitive identification of under which combination of spare parts' characteristics (i.e. spare parts demand, backorder costs, purchasing costs, lead time, …) AM represents the preferable sourcing option and when, instead, CM is to be preferred (Cantini et al., 2024). Based on this, we have considered it the suitable tool for our goal. Indeed, by developing two decision trees, one for the benchmark situation where AM and CM failure rates are assumed to be known and one for the situation where the failure rate uncertainties are considered, and comparing them, it will be possible to understand how the failure rate uncertainty affects the sourcing option decision and the AM/CM convenience areas.

To develop the decision trees, we have leveraged a decision tree algorithm, which is a supervised machine learning technique (Cantini et al., 2024). As for all the machine learning algorithms, a dataset is necessary to feed and train the decision tree algorithm. In this work we have carried out two parametric analyses to develop such dataset, one per each situation. Starting from the benchmark situation, (i.e. the situation in which the failure rates of AM and CM are assumed to be known precisely), Equations (1)–(4) have been used to determine the total costs of spare parts management for both AM and CM. More in detail, this has been done for different scenarios (specifically for 56,000 scenarios), where each scenario represents a different combination of the input parameters reported in Table 1.

The values reported in Table 1 and adopted for the parametric analysis have been chosen to cover different spare parts scenarios and they can be justified based on the literature as follows. Eight values of the unitary backorder cost c_b have been considered to cover scenarios of low, medium and high costs related to production losses, while five values of failure rate λ^{CM} have been selected to consider different part consumptions. More in detail, the values of the failure rates were chosen according to Knofius et al. (2020), and they cover situations where spare parts demand ranges from 4 parts per year to 1 part every 3 years.

Table 1
Parameters adopted in the parametric analysis.

Parameters	Value(s)		Unit
	CM	AM	
λ^x	0.005; 0.01; 0.02; 0.04; 0.08	$\frac{\lambda^{CM}}{5.2}$	1/weeks
L^x	2; 3; 4; 5; 6; 7; 8	0.5; 1; 1.5; 2	Weeks
r_p	–	1.5; 2; 2.5; 3; 3.5; 4; 4.5; 5; 5.5; 6	–
c_p^x	25; 50; 100; 200; 400	$c_p^{CM} \bullet r_p$	€
c_b	250; 500; 1000; 2000; 4000; 8000; 16,000; 32,000		€/week

Moreover, following the literature focusing on SLM as AM process and stainless steel as material (Sgarbossa et al., 2021), we have considered that the failure rate of AM λ^{AM} is 5.2 times lower than that of CM counterparts. The values of the lead time L^x, then, cover again situations characterized by short, medium and long procurement lead times. It is worth specifying that in this work we consider that parts are not produced internally but they are purchased from an external supplier. Considering the benefits of AM of reducing lead time, the values of the lead time for AM (L^{AM}) have been considered smaller than those of CM (L^{CM}). These values, as those for the unitary purchasing cost of CM parts c_p^{CM}, have been taken from Cantini et al. (2024). Again, also the values of purchasing costs of CM parts aim to cover different scenarios of low, medium, and high prices. Then, for the purchasing costs of AM parts c_p^{AM}, these are computed through the parameter r_p, which, following Sgarbossa et al. (2021), can be as high as six times. Additionally, again following Sgarbossa et al. (2021), the review period T^x has been set equal to the lead time L^x, both for AM and CM. Finally, following the literature, the holding cost rate h has been assumed constant and equal to 0.58% of the purchasing cost on a weekly basis: indeed, it is common practice to consider it equal 30% of the production cost on a yearly basis, which corresponds to 0.58% on a weekly basis (Azzi et al., 2014).

The same values of the input parameters reported in Table 1, then, have been used for the parametric analysis for the situation where the failure rates of AM and CM are unknown and they are characterized by a certain uncertainty. For each developed scenario, the total costs of spare parts management have been calculated using Equations (1), (5)–(7). Here, the failure rate uncertainties of AM and CM parts are needed. These, given the assumption that the exact value of the failure rate follows a truncated normal distribution N^x, can be defined by the standard deviation σ^x. In the following, this will be expressed as percentage of the expected value of the failure rate (λ^x). Following the material science approach that will be described in details in the next section, the standard deviation σ^x has been found to be equal to 48% and 21% for AM and CM parts, respectively.

3.3. Failure rate uncertainty determination

As briefly mentioned above, the failure rate uncertainty of AM and CM have been determined leveraging a material science approach. Following such material science approach and following Lolli et al. (2022), we have examined fatigue curves[2] obtained from laboratory specimens. Indeed, as described by Lolli et al. (2022), the mean time to failure (MTTF) of a specific part subject to a certain applied load F can be linked to the fatigue strength of a laboratory specimen subject to the same applied load F. Leveraging this relation, we have determined the failure rate uncertainty of AM and CM parts as follows. First, per each sourcing option (i.e. AM and CM), we have collected references (i.e. journal articles) reporting the fatigue curves of that sourcing option. Then, considering a certain applied load F^*, per each reference we have determined the fatigue strength reported. This led to the determination of different values of fatigue strengths (one per each reference) which correspond to an uncertainty in the expected value of the fatigue strength. Then, given the relation between the fatigue strength and the MTTF, we have converted this uncertainty into an uncertainty in the expected value of the MTTF. Thus, finally, given the relation between the MTTF and the failure rate, we converted the uncertainty in the MTTF into the uncertainty in the failure rate. We did this for each sourcing option, leading to a standard deviation of the failure rate of 48% and 21% for AM and CM parts, respectively. The procedure adopted is schematically reported in Fig. 2, where the diagonal lines represent the

[2] Fatigue curves report the average fatigue strengths of laboratory specimens (i.e. the number of cycles to failure) for different applied loads F (i.e. the loading conditions).

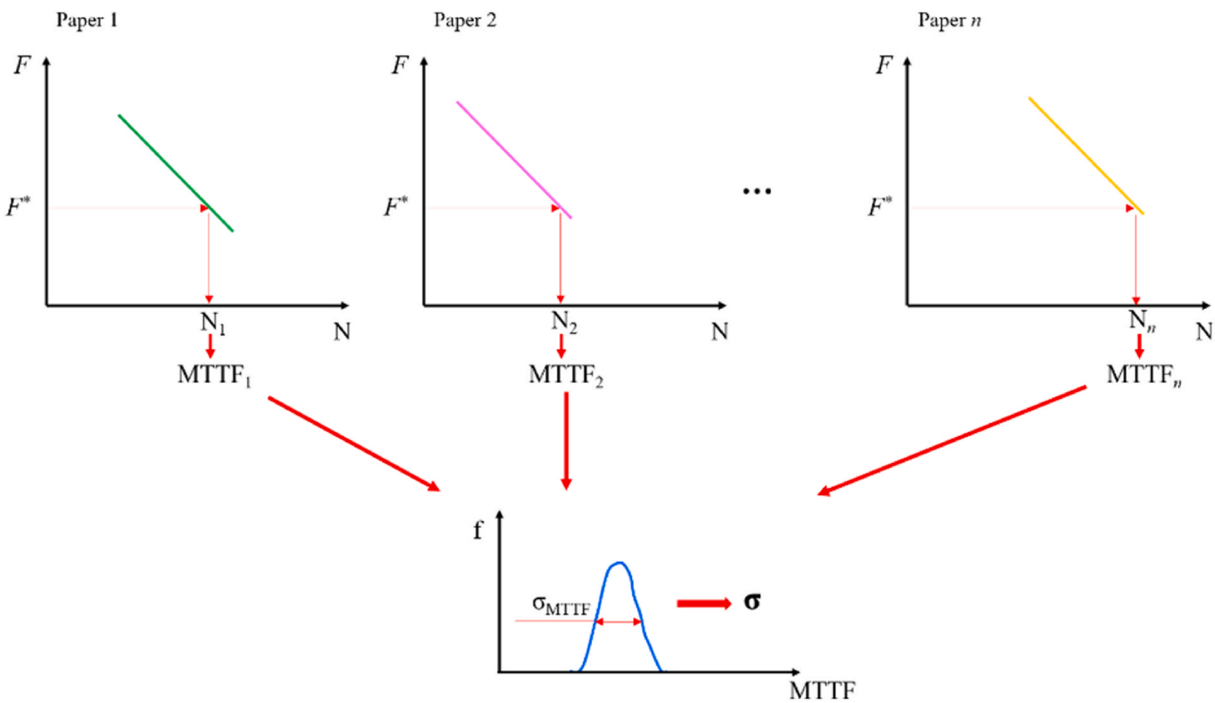

Fig. 2. Schematic representation of failure rate uncertainty determination.

fatigue curves.

3.4. Future situation

In the future situation, we consider that the tools for reducing AM failure rates uncertainties are adopted. Among the different possible tools available to reduce AM failure rate uncertainties (cf., e.g., Kim et al. (2018), Stavropoulos and Foteinopoulos (2018), Charalampous et al. (2020), Lee et al. (2021), Liu, M. et al. (2021), and Brennan et al. (2021) for comprehensive reviews), from an online discussion with practitioners working in the field, it has emerged that the main tools available to reduce the AM failure rate uncertainties are three, which are described in Table 2 together with the associated costs.

As discussed above, to implement these tools additional costs are needed, which further increase AM-related production costs. Therefore, to justify their adoption, each of these tools should reduce the AM failure rate uncertainties up to a level for which the reduced AM inventory management-related costs counterbalance the above-mentioned additional costs. In other words, for each of these tools, AM failure rate uncertainties should decrease up to a level for which the number of scenarios for which AM is convenient now that failure rate uncertainties reduction tools are implemented *at least* corresponds to the number of scenarios for which AM is convenient when no failure rate uncertainties reduction tools are implemented. To determine such threshold value of the AM failure rate uncertainties, we have selected parametric analysis as suitable methodology. Indeed, parametric analyses allow to develop several feasible scenarios and to evaluate the number of scenarios for which AM is the most convenient sourcing option. Therefore, by performing a parametric analysis per each potential value of AM failure rate uncertainty,[3] determining per each of them the number of scenarios for which AM is the most convenient sourcing option and comparing it with the number of scenarios for which AM is convenient when no failure rate uncertainties reduction tools are implemented, it is possible to determine such threshold value of AM failure rate. Indeed, this corresponds to the highest value of AM failure rate uncertainty for which the number of scenarios for which AM is convenient now that failure rate uncertainties reduction tools are implemented either matches or is greater than the number of scenarios for which AM is convenient when no failure rate uncertainties reduction tools are implemented.

It is worth mentioning that, to make the comparison consistent, the new parametric analyses use the same data used for the parametric analysis for the situation where no failure rate uncertainties reduction tools are implemented (cf. Section 3.2). Moreover, for each scenario, the most convenient sourcing option has been calculated using again Equations (1), (5)–(7), but this time the unitary purchasing cost of AM parts c_p^{AM} have been changed according to Table 2.

4. Results and discussions

In this section we present and discusses the results of our work. Particularly, Section 4.1 answers RQ1 (From an inventory management perspective, how do the failure rate uncertainties impact the sourcing option decision (AM/CM)?), while Section 4.2 answers RQ2 (Considering the tools to reduce AM failure rate uncertainties, what is the failure rate uncertainties reduction that each tool should achieve to justify the additional costs?).

4.1. Impact of failure rate uncertainties on the sourcing option decision

As described above, to determine how the failure rate uncertainties impact the sourcing option decision and the AM/CM convenience areas, two decision trees have been developed and then compared. The decision tree dealing with the benchmark situation (i.e. the situation where the failure rate uncertainties of AM and CM parts are neglected because the failure rates of AM and CM are assumed to be known precisely) is depicted in Fig. 3.

From the results, AM represents the preferable sourcing option almost 76% of the scenarios analyzed. Moreover, as it can be seen, the convenience of AM/CM depends on three main parameters, i.e. the lead time of AM and CM (L^{AM} and L^{CM}, respectively) and the purchasing cost ratio r_p. The other parameters considered and included in the model, i.e.

[3] Considering the fact that CM is a well-established manufacturing technology, we have assumed that AM failure rate uncertainty cannot decrease below the failure rate uncertainties of CM parts (i.e. 21%).

Table 2
Main tools available for AM uncertainties reduction, their description and associated costs.

Tool	Description	Additional costs
Porosity assessment	After production, the part is inspected with a CT scan. The detected porosity is then compared with a previously-built database: given a certain porosity content in input, the database provides the distribution of the expected value of the failure rate (i.e. failure rate uncertainty) as output	Additional costs of 150 €/piece for hardware and software; this cost is in line with what reported in the literature (du Plessis et al., 2018; Colorado Metallurgical Services, 2023)
In-situ monitoring	The production process is monitored in terms of melt pool. After production, the collected information are compared with a previously-built database: from the melt pool shapes and distribution, this suggests a distribution of the expected value of the failure rate (i.e. failure rate uncertainty)	20% increase in production costs to consider the costs necessary to purchase the equipment for in-situ monitoring + development of the database; this cost is in line with what reported in the literature (Colosimo et al., 2020)
Sacrificial testing	At least 3 additional parts are produced and tested. This allows to better evaluate the distribution of the failure rates	Additional costs for producing 3 parts and 100 €/piece to test the additional parts; this cost is in line with what reported in the literature (Colorado Metallurgical Services, 2023)

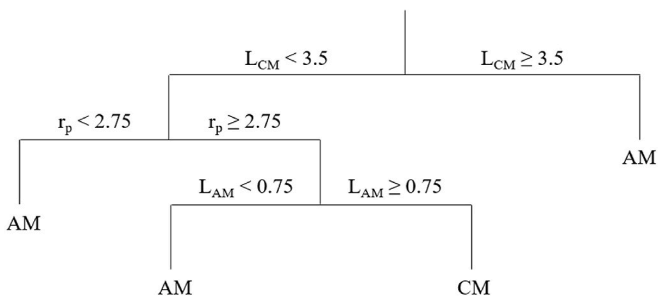

Fig. 3. Decision tree reporting the AM/CM convenience areas for the benchmark situation. Accuracy of the tree: 98.7%.

unitary backorder cost c_b and failure rate λ^x, instead, do not influence the decision.

From the analysis of the decision tree, three main areas of AM convenience can be identified. First, AM is always the preferable sourcing option when the lead time of CM is higher than 3.5 weeks. In this case, the much lower lead time of AM allows to reduce the inventory levels, balancing in this way its higher production costs. When, instead, the lead time of CM is lower than 3.5 weeks, the lower inventory levels achievable via AM are not enough alone to justify the choice of AM as sourcing option. Indeed, in these situations, AM is beneficial only if AM parts do not cost 2.75 times more than the CM counterparts. If this does not hold true and the AM parts cost more than 2.75 times the CM counterparts, then AM needs to be characterized by a very low lead time (lower than 0.75 weeks) to be convenient. These results represent the starting point of this work since they will be used as benchmark to determine the impact of the failure rate uncertainties on the sourcing option decision and the AM/CM convenience areas.

To do so, the areas of AM convenience just described need to be compared with those identified from the decision tree reported in Fig. 4. This represents the decision tree developed for the situation where the failure rate uncertainties are considered. Particularly, based on Section 2.3, AM parts are characterized by a standard deviation of the failure rate equal to 48%, while CM parts by a standard deviation of the failure rate equal to 21%.

In this case, the convenience of AM decreases from almost 76%–45.1% of the scenarios analyzed, showing the high negative impact that the higher failure rate uncertainties of AM play at AM disadvantage. Although this might be seen as an intuitive result, what is new is that the negative impact is quantified for the first time in the literature, and it is interesting observing how this impact is not negligible at all. This hence suggests that future efforts aiming to reduce AM failure rate uncertainties might be very beneficial, and we will elaborate on this in the following providing some preliminary analysis. Before doing that, however, it is interesting describing how the areas of convenience of AM change.

In the benchmark situation, we identified three main areas of convenience. The first one corresponds to the scenarios where the lead time of CM is higher than 3.5 weeks. When the failure rate uncertainties are considered, it is not enough anymore that the lead time of CM is higher than 3.5 weeks, but this needs to be coupled with a lead time of AM lower than 1.25 weeks. Indeed, to cover against a higher failure rate uncertainty, AM now needs higher inventory levels, hence limiting its main benefit when it comes to spare parts management. If the lead time of AM is higher than 1.25 weeks, then for AM to be convenient it is necessary that the lead time of CM is higher than 4.5 weeks and that the purchasing cost of AM parts is at maximum 2.75 times that of CM counterparts. Then, the second area of AM convenience identified in the benchmark situation corresponds to scenarios where the lead time of CM is lower than 3.5 weeks and the purchasing costs ratio is lower than 2.75. This area of convenience is also affected by the failure rate uncertainties. Indeed, for AM to be convenient is not enough anymore that those two conditions hold, but additionally AM parts need to have small lead times (lower than 1.25 weeks). Finally, the last area of AM convenience identified in the benchmark situation corresponds to the scenarios where the lead time of CM is lower than 3.5 weeks and where AM parts do not cost 2.75 times more than the CM counterparts only if the lead time of AM is lower than 0.75 weeks. However, when the failure rate uncertainties are considered, if the lead time of CM is lower than 3.5 weeks and the purchasing costs ratio is higher than 2.75, AM is never convenient, no matter its lead time. Table 3 summarizes the changes in AM areas of convenience when the failure rate uncertainties are

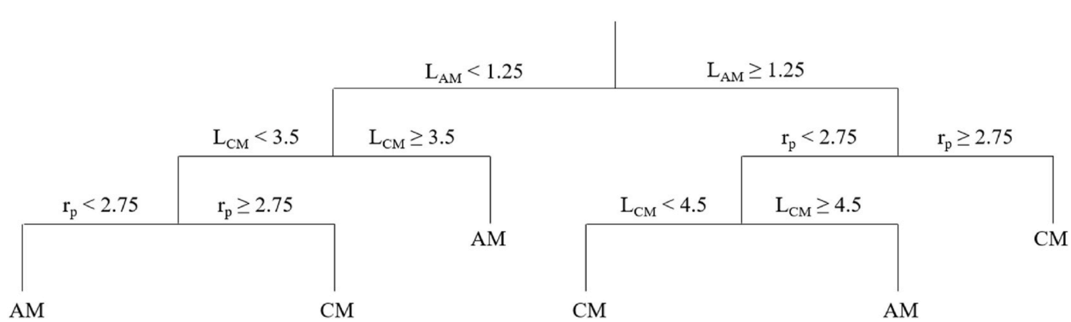

Fig. 4. Decision tree reporting the AM/CM convenience areas for the situation where failure rate uncertainties are considered. Accuracy of the tree: 97.3%.

Table 3
AM areas of convenience for the benchmark situation (i.e. when failure rates are assumed to be known precisely) and for the situation where failure rates are instead considered.

AM convenience areas	
Benchmark situation	**Uncertainties considered**
When $L^{CM} \geq 3.5$ weeks	Additional requirement $L^{AM} < 1.25$ weeks When $L^{CM} \geq 4.5$ weeks & $L^{AM} \geq 1.25$ weeks & $r_p < 2.75$
When $L^{CM} < 3.5$ weeks & $r_p < 2.75$	Additional requirement $L^{AM} < 1.25$ weeks
When $L^{CM} < 3.5$ weeks & $r_p \geq 2.75$ & $L^{AM} < 0.75$ weeks	Never convenient if $r_p \geq 2.75$

considered.

4.2. Tools to reduce AM failure rate uncertainties: to adopt or not to adopt?

Now that the impact of the failure rate uncertainties on the sourcing option and AM convenience areas has been described, we can elaborate on whether the newly developed tools for reducing AM failure rates uncertainties should be adopted or not. More in detail, we aim to shed lights on how much each of these tools should reduce AM failure rate uncertainties to render their adoption convenient. As discussed above, this implies finding per each tool the highest value of AM failure rate uncertainty for which the number of scenarios for which AM is convenient when the failure rate uncertainties reduction tools are implemented either matches or is greater than the number of scenarios for which AM is convenient when no failure rate uncertainties reduction tools are implemented (which was 45.1%). Fig. 5 elaborates on this: per each value of AM failure rate uncertainty potentially achievable when one of these reduction tools is implemented (X-axis), Fig. 5 depicts the number of scenarios where AM is convenient when such a reduction tool is adopted (Y-axis) and compares it with the threshold value of 45.1%, which is the number of scenarios for which AM is convenient when no failure rate uncertainties reduction tools are implemented. More in detail, the yellow line corresponds to the adoption of porosity assessment as a reduction tool, while the green line and the blue line correspond to the adoption of sacrificial testing and in-situ monitoring, respectively. It is worth reminding that in this work we consider that the values of AM failure rate uncertainty potentially achievable when a reduction tool is implemented could decrease from 48% (its current value, so no reduction achieved) to maximum 21%, which is the CM level that we assumed as a current plateau considering the high experience and data availability available for CM technologies. This explains the X-axis employed in Fig. 5.

From Fig. 5, three main things can be noted. First, that sacrificial testing does not represent a convenient tool to reduce the failure rate uncertainties of AM. Indeed, when considered, the number of scenarios for which AM is convenient never matches the threshold value and therefore the inventory management-related savings achievable are not enough to cover the costs of this tool. This can be explained considering the fact that sacrificial testing is a tool that is not specific for AM, but that has been used for more than hundred years to determine the failure rate of parts (even of CM). This implies that sacrificial testing is not a tool specifically tailored and designed for AM, and hence it does not tend to avoid AM's weaknesses (indeed it requires to produce additional parts, further increasing the production costs that are the main drawback of AM). This was also highlighted by Trivedi et al. (2018), who stated that the use of additional testing represents a limitation for AM and that practitioners hence tend to opt for CM. Then, porosity assessment and in-situ monitoring instead can both convenient tools for decreasing the failure rate uncertainties. More in detail, the former needs to reduce the failure rate uncertainty to a value of at least 43% to cover the additional costs, while the latter to 42%. Practitioners and researchers in the material science field have now for the first time an understanding of what is the minimum requirement in terms of failure rate uncertainty reduction for porosity assessment and in-situ monitoring to be convenient and they can work towards ensuring such minimum values. Moreover, Fig. 5 can preliminary support practitioners in the decision of whether adopting porosity assessment or in-situ monitoring, showing which is the tool ensuring the widest spread of AM (i.e. the highest number of scenarios in which AM is convenient) for the achievable failure rate uncertainty reduction. In the light of this, it can be observed that there is a cross-over point at a failure rate

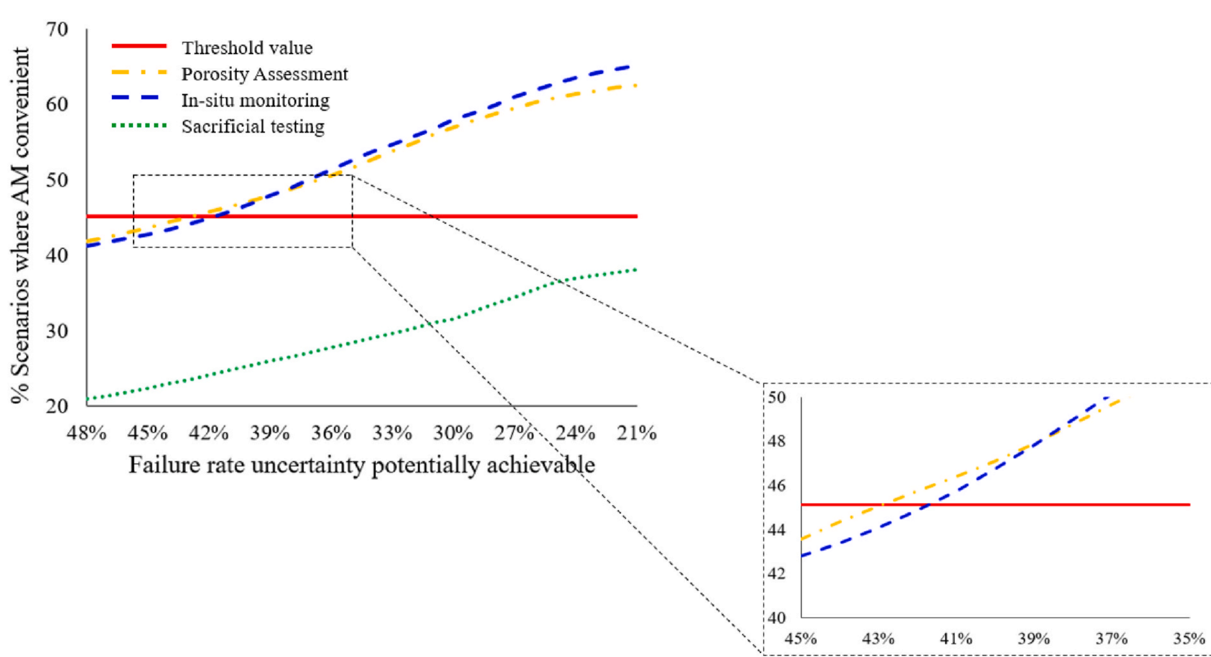

Fig. 5. Percentage of scenarios where AM is convenient when failure rate uncertainties reduction tools are implemented considering the different values of failure rate uncertainty potentially achievable.

uncertainty of 38%: before this value, if porosity assessment and in-situ monitoring reduce the failure rate uncertainty to the same value, porosity assessment should be adopted, while after this value (considering again that both reduce the failure rate uncertainty to the same value), in-situ monitoring becomes the preferable tool to reduce the failure rate. These are however just preliminary indications, and we soon elaborate better on this providing more detailed indications of when porosity assessment should be preferred over in-situ monitoring and vice versa, linking such decision also to the different spare parts characteristics. More in detail, when doing this, we also consider more realistic situations where the values of AM failure rate uncertainty achievable with porosity assessment can differ from those achievable with in-situ monitoring.

Before doing this, however, we want to elaborate on the economic implications of adopting porosity assessment and in-situ monitoring as tools to reduce AM failure rate uncertainties. More in detail, we want to understand what the savings would be achievable in terms of total spare parts management costs C_{tot} if these tools are introduced to understand whether their adoption is really worthy or not. For the sake of clarity, the savings achievable are meant as difference in total spare parts management costs C_{tot} with respect to the situation where failure rate uncertainties are considered but no failure rate uncertainties reduction tools are implemented. Fig. 6 elaborates on this distinguishing between porosity assessment (on the left) and in-situ monitoring (on the right): per different values of AM failure rate uncertainty potentially achievable by the reduction tool being considered (X-axis), it depicts the savings achievable (Y-axis). For the sake of clarity, negative savings imply that the adoption of the tool under consideration is not convenient. It is worth clarifying that sacrificial testing is not considered in Fig. 6 since, as shown in Fig. 5, it does not represent a suitable alternative.

As it can be seen, besides starting observing savings for AM failure rate uncertainties lower than 40% (as found in Fig. 5), it is interesting noting that the savings achievable are not negligible, with savings that can be almost as high as 1000 euros in some cases: given that these savings are for single stock keeping units and that companies usually have to deal with thousands of spare parts, the savings achievable if AM failure rate reduction tools are adopted are definitely not negligible. This proves the relevance of this second part of the work and calls for a more detailed and thorough understanding of which tool to reduce AM failure rate uncertainties should be adopted considering the AM failure rate reduction achievable and spare parts characteristics. Indeed, from the combination of Figs. 5 and 6 it is not possible to understand when one tool is to be preferred over the over: while Fig. 5 shows that in-situ monitoring overall leads to a higher spread of AM (i.e. a higher number of scenarios where AM is convenient), Fig. 6 depicts that, when porosity assessment and in-situ monitoring reduce the AM failure rate uncertainty to the same value, porosity assessment can lead to higher savings. Therefore, it is not clear when to adopt porosity assessment or in-situ monitoring.

To this aim, we have performed a new decision tree analysis to support the identification of such porosity assessment/in-situ monitoring convenience areas. The resulting decision tree is reported in Fig. 7, and it has been derived from the parametric analysis adopted to develop Fig. 5 and described in Section 3.4.

As it can be seen, there are some scenarios where, no matter the tool adopted, CM still represents the preferable sourcing option. This is the case when either the difference between the lead times of CM and AM are low (especially if the failure rates are low) or, when this is high, when neither of the tools have high performance in terms of AM failure rate uncertainties reduction. The former case is similar to and aligned with what found in Fig. 4 when analysing the AM/CM convenience areas for the situation where failure rate uncertainties are considered. The latter case, instead, provides a clearer target for researchers and practitioners working on the material science field to understand how much the AM failure rate uncertainty should be reduced to increase AM adoption in the spare parts management field. However, it is interesting noting that, contrarily to what one might expect, the AM failure rate uncertainty reduction achievable by these tools does not represent the main driver of the decision of whether to adopt any tool and, if so, which one. Indeed, $\sigma_{porosity}$ and $\sigma_{in-situ}$ do not represent the first parameter met in the decision tree, but, on the contrary, they appear in a quite low position: this means that their impact on the decision-making process is less relevant than other parameters such as the ratio between AM and CM unitary purchasing costs r_p and the lead time of CM parts L_{CM}. This implies that, in some scenarios, investing substantially to improve the performance of one specific tool to reduce AM failure rate uncertainties is not convenient at all since this might never be preferable to the other tool. This is an interesting insight for firms that have already invested or are planning to invest in a single specific tool to reduce AM failure rate uncertainty and to adopt it for all the spare parts they are managing, hence trying to adopt a "one-fits-all" solution. Just as an example, this is the case for spare parts characterized by a ratio between AM and CM unitary purchasing costs r_p greater than 3, lead time of CM parts L_{CM} lower than 6 weeks, lead time of AM parts L_{AM} lower than 0.75 weeks and failure rates λ^{CM} lower than 0.009 1/weeks: no matter on the AM failure rate uncertainties reduction achievable via porosity assessment and in-situ monitoring, the former will always be preferable. Therefore, the adoption of one tool to reduce AM failure rate uncertainties does not

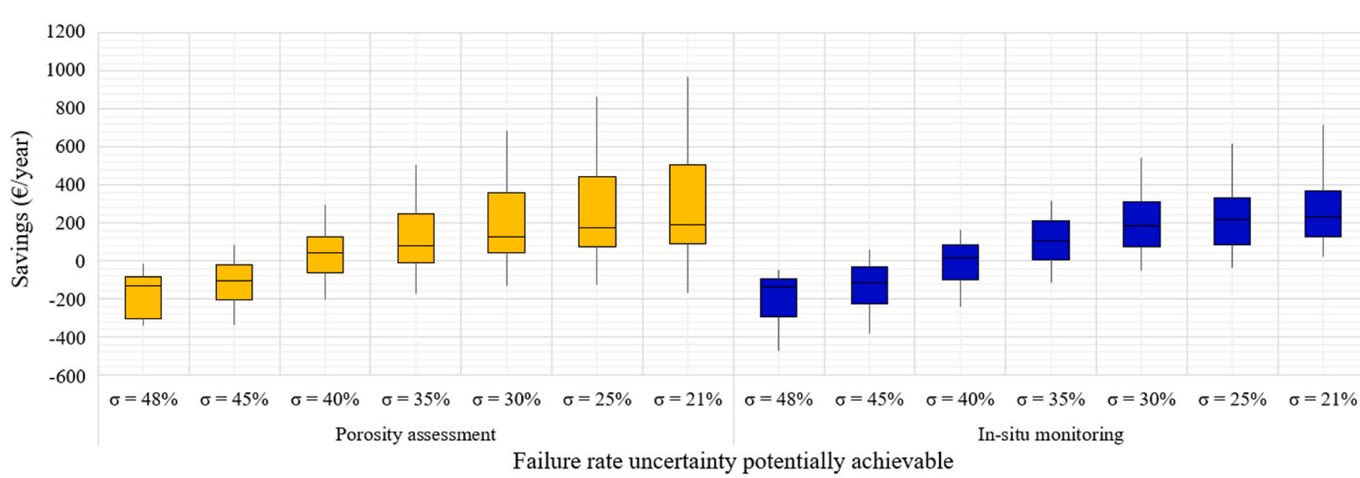

Fig. 6. Savings (€/year) distribution for porosity assessment and in-situ monitoring considering different AM failure rate uncertainty potentially achievable by each reduction tool. Notably, per each failure rate uncertainty, the difference between the savings achievable with the two reduction tools is statistically significant since the p-values obtained from both the *t*-test and the single factor ANOVA are all lower than 0.001.

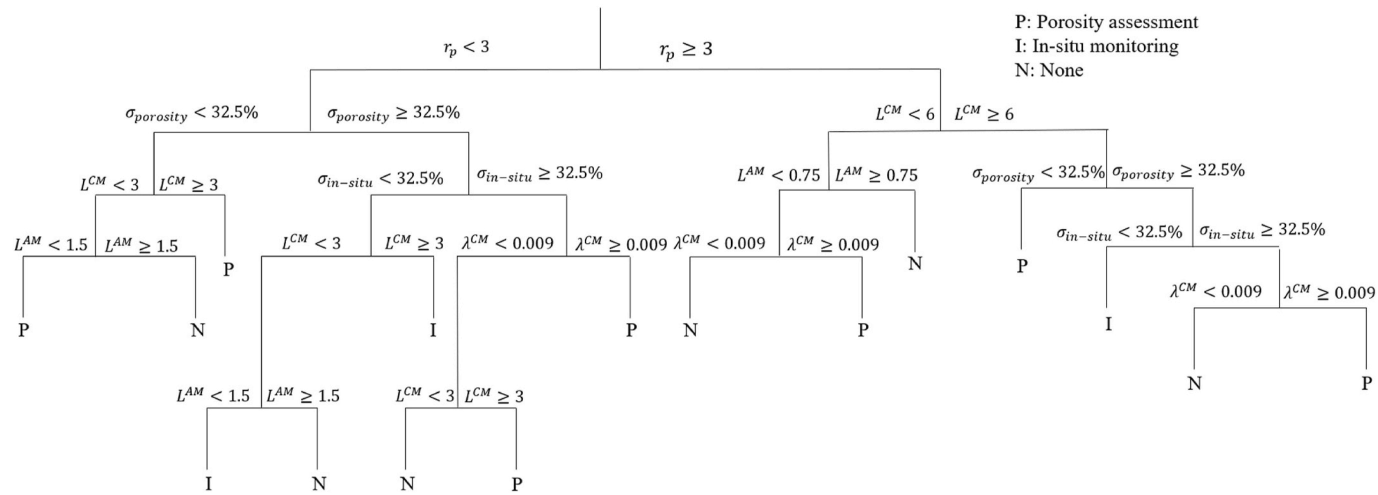

Fig. 7. Decision tree reporting the porosity assessment/in-situ monitoring convenience areas; "None" means that no matter the tool adopted, CM is always the preferred sourcing option; $\sigma_{porosity}$ and $\sigma_{in-situ}$ stands for the AM failure rate uncertainty achievable adopting porosity assessment and in-situ monitoring, respectively. Accuracy of the tree: 95.6%.

exclude the other, and a firm should rather adopt both in a complementary manner, and which one to chose depends on the characteristics of the spare parts under considerations. However, if one has to choose, overall porosity assessment is currently to be preferred, which is in line with the higher savings achievable (cf. Fig. 6). Nevertheless, things might change in the future due to the technological advancements for in-situ monitoring, which is expected to experience lower implementation costs.

5. Conclusions, theoretical and practical contributions, and future research

We conclude the work in Section 5.1, we elaborate on the theoretical and practical contributions of this work in Section 5.2, and we discuss future research in Section 5.3.

5.1. Conclusions

Thanks to the possibility to produce parts with reduced lead times (even on-demand) and the consequent inventory level reduction, AM has gained wide interest over the last years in the world of spare parts. However, its spread has been limited, mainly due to two main drawbacks: high production costs and high failure rate uncertainties. While the impact of the former on the sourcing option decision (i.e. whether to produce spare parts using AM or CM) has been widely treated in the literature, the same cannot be said for the latter, with no extensive works available in the literature. With this work, we aim to fill this gap, elaborating on the impact of failure rate uncertainties on the sourcing option decision. To do so, we have leveraged a multi-disciplinary approach, where knowledge from the material science field was used to derive realistic values of the failure rate uncertainties. Through the comparison with a benchmark situation where no failure rate uncertainties where considered, we have observed that the higher failure rate uncertainty of AM compared to that of CM penalizes AM heavily. Indeed, in the benchmark situation, AM was the most cost-effective option 76% of the scenarios analyzed, while when the failure rate uncertainties were considered the number of scenarios where AM was the preferable sourcing option decreased to 45.1%. Moreover, we also observed how AM convenience areas changed. When no failure rate uncertainties are considered, AM is always convenient when L^{CM} is high; whereas, when L^{CM} is low, for AM to be convenient the ratio between AM and CM unitary purchasing costs r_p needs to be low. If this is high, L^{AM} is required to be very low for AM to be convenient. When failure rate uncertainties are considered, then, these AM convenience areas change: it is not enough anymore for L^{CM} to be high, but L^{AM} is required to be low. If this is high, r_p needs to be low. Finally, AM is not convenient anymore if r_p is high.

Finally, for the first time in the literature, we have also considered a future scenario where tools to reduce AM failure rate uncertainties are adopted. Through a discussion with experts in the sector, we have identified three main tools to reduce the failure rate uncertainties of AM and the associated costs: porosity assessment, in-situ monitoring, and sacrificial testing. We have then evaluated how much each of these tools should bring in terms of reduced AM failure rate uncertainties so that the corresponding inventory management-related savings balance the required additional costs. From the analysis, we showed that only two of these tools are worth being adopted, i.e. porosity assessment and in-situ monitoring, while the required investments for sacrificial testing are too high. Then, we have shown that the savings achievable by adopting such tools are significant, being almost as high as 1000 euros per year for single SKU in some cases. Finally, once proven the relevance of such analysis, we have elaborated on identifying when one tool should be preferred to the other based on spare parts characteristics (i.e. spare parts demand, lead times, …). Here, we have observed that there are still some scenarios where, no matter the tool adopted, CM still represents the preferable sourcing option: these correspond to the scenarios where either the difference between the lead times of CM and AM are low (especially if the failure rates are low) or, when this is high, when neither of the tools have high performance in terms of AM failure rate uncertainties reduction. Then, we have also observed that a "one-fits-all" solution is not applicable when it comes to the tools for reducing AM failure rate uncertainties: in some scenarios, no matter how much a certain tool (either porosity assessment or in-situ monitoring) is able to reduce AM failure rate uncertainty, this tool might never be preferable to the other one.

5.2. Theoretical and practical contributions

This work contributes to both theory and practice. Dealing with the theory, as previously highlighted (cf. Section 2), this work represents the first work to thoroughly investigate how failure rate uncertainties impact the sourcing option decision for spare parts. As shown by the results of this work, the impact of failure rate uncertainties on the sourcing option decision are everything but negligible: the fact that this topic has been neglected by the literature so far represented a quite substantial literature gap that this work has filled. Additionally, the theoretical contribution of this work was not just limited to fill this literature gap, but also to extend the research boundaries within the operations management field suggesting new research streams. Indeed, this work leverages the recent advances from the material science literature in terms of failure rates and the different tools to reduce them, and elaborates on the implications that their adoption would have for spare parts management. As we will better see in the next section on future research, this interdisciplinary approach opens up new research opportunities for operations management. Additionally, this interdisciplinary approach affects not only the operations management literature, but also that in the material science field as researchers in the material science field can leverage this work to have an indication of how much each of the different tools should reduce AM failure rate uncertainties to be convenient, and they can work towards making such reduction feasible.

The implications for practice are also substantial. First, by filling the literature gap describe above, this work supports spare parts managers in identifying correctly whether they should adopt AM or CM spare parts. Indeed, by adopting the models currently available in the literature that do not consider the failure rate uncertainties, they would have risked to adopt the wrong sourcing option, incurring in higher spare parts management costs. Thanks to this work, instead, they have a correct indication of whether they should adopt AM or CM. Additionally, thanks to the decision tree developed (Fig. 4), they have now a tool that clearly identifies AM and CM areas of convenience: to identify whether they should adopt AM or CM spare parts, they do not have to implement any complex mathematical model, but they can leverage the simple decision tree, which is an easy-to-use graphic tool that quickly reveals the preferable sourcing option. This is expected to highly simplify the selection of the preferable sourcing option since spare parts managers have now access to clear indication and guidelines on when AM spare parts should be preferred to CM and vice versa. Furthermore, another practical implication deriving from this work arises from the analysis on the tools to reduce AM failure rate uncertainties: practitioners have now access for the first time to a thorough analysis of how much the different tools to reduce AM failure rate uncertainties should reduce AM failure rate uncertainties to justify their adoption. Additionally, from this analysis, they can also identify which is the best tool to reduce AM failure rate uncertainties given a certain reduction and certain spare parts characteristics. In this way, they are able to understand whether investing in equipment and techniques to reduce the failure rate uncertainties would reduce their spare parts management costs or not.

5.3. Future research

Researchers can use this work as a milestone for future research, where they overcome the limitations. First, they could extend this work to different materials and AM processes to provide a complete and thorough support to practitioners. Notably, the methodology herein adopted allows to easily do this as it just requires to change the purchasing costs, the lead times and the failure rates according to the material and AM process considered. Additionally, this work could be extended to include also other tools to reduce AM failure rate uncertainties to provide a comprehensive and exhaustive overview. As an example, morphology assessment and microstructural assessment could be considered, but also other tools reported in the literature (cf. Section 3.4). Then, researchers could extend this work to situations where AM is used in safety-critical applications. Indeed, AM has recently started being used in such applications (DNV, 2022; Graves et al., 2021), and hence such a future work would be extremely relevant in the future. Here, as discussed above, researchers should consider that failure rate uncertainties impact not only inventory management-related costs but also the costs associated with the quality control procedures required. Moreover, researchers could extend this work considering the technological advancements that in-situ monitoring and porosity assessment will experience in the future. These, in fact, might decrease the costs associated with their implementation, and hence researchers could evaluate the impact of such changes on the results herein found. Furthermore, following the recent literature (Singh et al., 2022; Ransikarbum et al., 2020), researchers could extend the focus of this work from single objective (i.e. economic) to multi objective, considering different criteria (e.g. economic, environmental, social). Finally, researchers could perform all the analyses carried out in this work and suggested as future research but adopting a multi-item approach, where AM spare parts can be produced internally instead of being outsourced.

CRediT authorship contribution statement

Mirco Peron: Writing – original draft, Supervision, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Antonio Maria Coruzzolo:** Writing – original draft, Data curation. **Rob Basten:** Writing – original draft, Methodology, Data curation. **Nils Knofius:** Validation, Data curation, Conceptualization. **Francesco Lolli:** Visualization, Validation. **Fabio Sgarbossa:** Visualization, Validation.

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Appendix A

Table A1
Literature review analysis. Notice that only papers adopting a quantitative approach have been considered.

Article	Main focus and findings	AM and CM characteristics						Limitations and gaps
		Costs		Failure rate		Failure rate uncertainties		
		Similar	Different	Similar	Different	Considered	Not considered	
Khajavi et al. (2014)	Focus on AM adoption in aircraft spare parts supply chain	N/A	N/A	N/A	N/A		X	- No comparison between AM and CM so no support in the sourcing option (AM/CM) decision

(continued on next page)

Table A1 (*continued*)

Article	Main focus and findings	AM and CM characteristics						Limitations and gaps
		Costs		Failure rate		Failure rate uncertainties		
		Similar	Different	Similar	Different	Considered	Not considered	
Li et al. (2019)	AM spare parts supply chain	N/A	N/A	N/A	N/A		X	- No comparison between AM and CM so no support in the sourcing option (AM/CM) decision
Xu et al. (2021)	AM spare parts supply chain	N/A	N/A	N/A	N/A		X	- No comparison between AM and CM so no support in the sourcing option (AM/CM) decision
Liu et al. (2014)	AM vs CM in aircraft spare parts supply chain Inventory level reduction with AM up to 70%	N/A	N/A	N/A	N/A	N/A	N/A	- Comparison AM – CM based only on inventory levels, no costs considered
Sirichakwal and Conner (2016)	AM vs CM for spare parts inventory management AM reduces holding costs		X (CM > AM)	X			X	- Comparison AM – CM based only on inventory levels and costs; no other relevant costs (e.g. production) are considered - CM parts are commonly known to be less expensive than AM - AM and CM parts are commonly known to have different failure rates -No failure rate uncertainties considered despite the reported effect on inventory levels and costs
Ghadge et al. (2018)	AM vs CM n aircraft supply chain inventory levels and holding costs AM leads to a reduction of mean stock up to 85%	N/A	N/A	X			X	- Comparison AM – CM based only on inventory levels and costs; no other relevant costs (e.g. production) are considered - AM and CM parts are commonly known to have different failure rates - No failure rate uncertainties considered despite the reported effect on inventory levels and costs
Li et al. (2016)	AM vs CM spare parts supply chain AM is preferable as sourcing option if inventory costs are the only costs to be considered, otherwise CM		X (CM < AM)	X			X	- AM and CM parts are commonly known to have different failure rates - No failure rate uncertainties considered despite the reported effect on inventory levels and costs
Khajavi et al. (2018)	AM – CM switchover point given different AM production costs High impact of AM production costs on switchover point and great attention should be given also to the raw material costs		X (CM < AM)	X			X	- AM and CM parts are commonly known to have different failure rates - No failure rate uncertainties considered despite the reported effect on inventory levels and costs
Knofius et al. (2019)	AM vs CM spare parts supply chain AM is convenient when backorder costs are high, the difference between AM and CM lead times is high, and when the difference between AM and CM production/purchasing costs is low		X (CM < AM)	X			X	- AM and CM parts are commonly known to have different failure rates - No failure rate uncertainties considered despite the reported effect on inventory levels and costs
Heinen et al. (2019)	Switch from CM to AM for spare parts AM – CM switchover point defined for different AM production costs		X	X			X	- AM and CM parts are commonly known to have different failure rates - No failure rate uncertainties considered despite the reported effect on inventory levels and costs
Zhang et al. (2019)	AM vs CM spare parts supply chain considering AM on demand AM is limited by high costs and is suitable only for small parts		X (CM < AM)	X			X	- AM and CM parts are commonly known to have different failure rates - No failure rate uncertainties considered despite the reported effect on inventory levels and costs
Rinaldi et al. (2021)	AM vs CM supply chain CM is preferable due to the lower costs		X (CM < AM)	X			X	- AM and CM parts are commonly known to have different failure rates

(*continued on next page*)

Table A1 (*continued*)

Article	Main focus and findings	AM and CM characteristics						Limitations and gaps
		Costs		Failure rate		Failure rate uncertainties		
		Similar	Different	Similar	Different	Considered	Not considered	
								- No failure rate uncertainties considered despite the reported effect on inventory levels and costs
Mecheter et al. (2024)	AM vs CM spare parts supply chain The ratio between AM and CM parts costs vary depending on their complexity AM is cost-effective for spare parts with high geometric complexity, whereas CM is more economical for larger parts with simpler geometries		X	X			X	- AM and CM parts are commonly known to have different failure rates - No failure rate uncertainties considered despite the reported effect on inventory levels and costs
Song and Zhang (2020)	AM vs CM spare parts supply chain considering AM on-demand and insourced printers Dual sourcing is preferable to pure AM/CM sourcing		X (CM < AM)	X			X	- AM and CM parts are commonly known to have different failure rates - No failure rate uncertainties considered despite the reported effect on inventory levels and costs
Roozkhosh et al. (2024)	AM vs CM spare parts supply chain Dual sourcing is preferable to pure AM/CM sourcing		X (CM < AM)		X (CM < AM)		X	- CM parts are considered to have a lower failure rate than AM parts, which does not hold true given the recent AM technological advancements - No failure rate uncertainties considered despite the reported effect on inventory levels and costs
Knofius et al. (2020)	AM vs CM spare parts supply chain Dual sourcing is preferable to pure AM/CM sourcing		X (CM < AM)		X (CM < AM)		X	- CM parts are considered to have a lower failure rate than AM parts, which does not hold true given the recent AM technological advancements - No failure rate uncertainties considered despite the reported effect on inventory levels and costs
Westerweel et al. (2018)	AM vs CM spare parts supply chain adopting a lifecycle cost analysis to find breakeven point between CM or AM parts		X		X (CM < AM)		X	- CM parts are considered to have a lower failure rate than AM parts, which does not hold true given the recent AM technological advancements - No failure rate uncertainties considered despite the reported effect on inventory levels and costs
Westerweel et al. (2021)	AM vs CM spare parts supply chain for remote locations AM is preferable when the site of use is difficult to reach		X		X (CM < AM)		X	- CM parts are considered to have a lower failure rate than AM parts, which does not hold true given the recent AM technological advancements - No failure rate uncertainties considered despite the reported effect on inventory levels and costs
Sgarbossa et al. (2021)	AM vs CM spare parts supply chain Decision-tree based decision support system for selecting AM or CM for spare parts inventory management Multidisciplinary approach to determine AM and CM failure rates		X		X		X	- No failure rate uncertainties considered despite the reported effect on inventory levels and costs
Cantini et al. (2024)	AM vs CM spare parts supply chain Decision-tree based decision support system for selecting AM or CM for spare parts configuration Different ratios between AM and CM failure rates		X		X		X	- No failure rate uncertainties considered despite the reported effect on inventory levels and costs
Peron et al. (2024)	AM vs CM supply chain considering the impact of electricity prices and raw materials availability Decision-tree based decision support system for selecting AM or CM sourcing option		X		X		X	- No failure rate uncertainties considered despite the reported effect on inventory levels and costs

(*continued on next page*)

Table A1 (*continued*)

Article	Main focus and findings	AM and CM characteristics						Limitations and gaps
		Costs		Failure rate		Failure rate uncertainties		
		Similar	Different	Similar	Different	Considered	Not considered	
Van Wingerden et al. (2017)	Effect of failure rate uncertainties on inventory levels and costs As the failure rate increases, the inventory levels and costs increase non-negligibly	N/A	N/A	N/A	N/A	X		- No comparison between AM and CM so no support in the sourcing option (AM/CM) decision
Peron et al. (2022)	Effects of failure rate uncertainties on AM/CM sourcing option decision Considering the failure rate uncertainties highly reduce AM convenience		X		X	X		- Preliminary study with only few scenarios considered (no extensive analysis) - No considerations on adoption of AM failure rate reduction tools
This work	Effects of failure rate uncertainties on AM/CM sourcing option decision overcoming literature limitations (i.e. we consider different costs and failure rates between AM and CM parts and we consider failure rate uncertainties) For the first time we elaborate also on the adoption of AM failure rate reduction tools		X		X	X		–

Appendix B

In proving that the higher the failure rate uncertainty, the higher the total spare parts management costs C_{tot}, we do not distinguish between the sourcing option (i.e. AM or CM), and hence, contrarily to the main body of the work, we do not use the superscript x in the following.

To show that an increase in the failure rate uncertainty leads to an increase in the total costs, we show that the holding and backorder costs increase with an increase in the failure rate uncertainty, while the purchasing costs remain the same.

Starting from the holding costs. Following Van Wingerden et al. (2017), the holding costs can be rewritten according to Equation (B1):

$$C_h = h \bullet c_p \bullet \sum_{y=0}^{S-1} (S-y) \bullet P_{\lambda,T+L,y} = h \bullet c_p \bullet E\left[\left(S - Y^{ud}\right)^+\right] \tag{B1}$$

Where Y^{ud} is the demand during the time period $T + L$, which is Poisson distributed with unknown mean. Based on this equation, to prove that the holding costs increase with an increase in the failure rate uncertainty, we can prove that $h \bullet c_p \bullet E\left[\left(S - Y^{ud}\right)^+\right]$ increases with an increase in the failure rate uncertainty. To do so, we can leverage the findings of van Wingerden et al. (2017), who show that a demand rate characterized by a higher variance (i.e. uncertainty) leads to a distribution of the demand during lead time that is stochastically larger[4] than that derived from a demand rate characterized by a lower variance (i.e. uncertainty). Given the equivalence between the demand rate and the failure rate, we can export their findings to our case. This is the key for proving that the holding costs increase with an increase in the failure rate uncertainty. In fact, by considering two truncated normal distributions of the expected value of the failure rate λ, namely N_1 and N_2, with the same mean (i.e., $E[N_1] = E[N_2]$) but with N_1 being characterized by a higher variance than N_2, according to Proposition 2.2 in van Wingerden et al. (2017), we have that the demand during lead time associated to N_1, i.e. Y_1^{ud}, is stochastically larger than the demand during lead time associated to N_2, i.e. Y_2^{ud}:

$$Y_1^{ud} \geq_{ic} Y_2^{ud} \tag{B2}$$

From this, based on the fact that $Y_1^{ud} \geq_{ic} Y_2^{ud}$ if, and only if:

$$E\left[f\left(Y_1^{ud}\right)\right] \geq E\left[f\left(Y_2^{ud}\right)\right] \tag{B3}$$

for all convex functions $f\left(Y^{ud}\right)$, we can show that the holding costs increase increasing the failure rate uncertainty by defining the function $f\left(Y^{ud}\right)$ as

$$f\left(Y^{ud}\right) = h \bullet c_p \bullet \left(S - Y^{ud}\right)^+ \tag{B4}$$

In this case, in fact, we have that

$$h \bullet c_p \bullet E\left[\left(S - Y_1^{ud}\right)^+\right] \geq h \bullet c_p \bullet E\left[\left(S - Y_2^{ud}\right)^+\right] \tag{B5}$$

and this, based on Eq. (B1), corresponds to demonstrating that a stochastically larger Poisson distributed demand (i.e. a distribution with a greater variance) leads to higher holding costs.

Dealing with the backorder costs. Again, we want to show that a higher failure rate uncertainty leads to higher backorder costs. Also for this, we need to keep in mind the just-mentioned findings of van Wingerden et al. (2017) (i.e. a failure rate characterized by a higher uncertainty leads to a distribution of the demand during lead time that is stochastically larger). We can rewrite Eq. (3) as:

[4] A random variable V_1 is stochastically larger than a random variable V_2 if $Pr\{V_1 \geq x\} \geq Pr\{V_2 \geq x\}$ for all x (Pr { • } denotes the probability of an event).

$$C_b = c_b \bullet \sum_{y=S+1}^{\infty} (y - S) \bullet P_{\lambda,T+L,y} = c_b \bullet \left(\lambda \bullet (T+L) - S + \sum_{y=0}^{S-1} (S-y) \bullet P_{\lambda,T+L,y} \right) \tag{B6}$$

Considering two failure rates characterized by different uncertainties and same mean values, we define $C_{b,1}$ and $C_{b,2}$ as the backorder costs for the failure rates characterized by high and low uncertainties, respectively. We want to show that $C_{b,1} \geq C_{b,2}$. This can be proved in the following:

$$C_{b,1} - C_{b,2} \geq 0 \tag{B7}$$

$$C_{b,1} - C_{b,2} = c_b \bullet \left(\lambda_1 \bullet (T+L) - S + \sum_{y=0}^{S-1} (S-y) \bullet P_{\lambda_1,T+L,y} \right) - c_b \bullet \left(\lambda_2 \bullet (T+L) - S + \sum_{y=0}^{S-1} (S-y) \bullet P_{\lambda_2,T+L,y} \right) = c_b \bullet \left(\lambda_1 \bullet (T+L) - \lambda_2 \bullet (T+L) + \sum_{y=0}^{S-1} (S-y) \bullet P_{\lambda_1,T+L,y} - \sum_{y=0}^{S-1} (S-y) \bullet P_{\lambda_2,T+L,y} \right) \tag{B8}$$

In Eq. (B8), the terms $\lambda_1 \bullet (T+L)$ and $\lambda_2 \bullet (T+L)$ are however equivalent since we consider the distribution of the failure rate to be characterized by the same mean value, therefore Eq. (B8) becomes

$$C_{b,1} - C_{b,2} = c_b \bullet \left(\sum_{y=0}^{S-1} (S-y) \bullet P_{\lambda,T+L,y} - \sum_{y=0}^{S-1} (S-y) \bullet P_{\lambda,T+L,x} \right) \tag{B9}$$

Equation (B9) can then be rewritten as follows considering Equation B1

$$C_{b,1} - C_{b,2} = c_b \bullet E\left[\left(S - Y_1^{ud}\right)^+\right] - c_b \bullet E\left[\left(S - Y_2^{ud}\right)^+\right] \tag{B10}$$

And, considering Equation (B5), we can finally prove that an increase in the variance (i.e. uncertainty) of the failure rate leads to an increase in the backorder costs, i.e. that $C_{b,1} - C_{b,2} \geq 0$.

Finally, the purchasing costs. The purchasing costs will not change but they remain the same with an increase in failure rate uncertainty. To show that they remain the same, we leverage again on the findings of van Wingerden et al. (2017). Equation (4) (main text) reporting the purchasing costs can be rewritten as

$$C_p = c_p \bullet \sum_{y=0}^{\infty} y \bullet P_{\lambda,T,y} = c_p \bullet E\left[Y^{ud+}\right] \tag{B11}$$

Considering two failure rates characterized by different uncertainties and same mean values, we define $C_{p,1}$ and $C_{p,2}$ as the purchasing costs for the failure rates characterized by high and low uncertainties, respectively. We want to show that $C_{p,1} = C_{p,2}$. To prove this, we can refer to the above-mentioned fact that the failure rates characterized by a higher uncertainty lead to a distribution of the demand during lead time that is stochastically larger. Named N_1 and N_2 the distribution of the expected value of the failure rate λ, with the same mean (i.e., $E[N_1] = E[N_2]$) but with N_1 being characterized by a higher variance (i.e. uncertainty) than N_2, we know from proposition 2.2 of van Wingerden et al. (2017) that the demand during lead time associated to N_1, i.e. Y_1^{ud}, and the demand during lead time associated to N_2, i.e. Y_2^{ud}, are linked as follows:

$$Y_1^{ud} \geq_{ic} Y_2^{ud} \textit{ and } E\left[Y_1^{ud}\right] = E\left[Y_2^{ud}\right] \tag{B12}$$

Therefore, $C_{p,1} = C_{p,2}$.

Concluding, we have proved that the higher the failure rate uncertainty, the higher the holding and backorder costs, while no changes occur in the purchasing costs. Thus, we can conclude that the higher the failure rate uncertainties, the higher the total spare parts management costs.

Data availability

Data will be made available on request.

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