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Insourcing additive manufacturing for spare parts production: is it profitable? An extensive analysis and the proposal of a Decision Support System

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ABSTRACT

Recently, Additive Manufacturing (AM) has gained significant interest as promising technology for spare parts production. Unlike Conventional Manufacturing (CM), insourcing AM machine(s) enables the production of spare parts on demand, which in turn reduces inventory levels. However, AM is characterised by high costs, primarily associated with the purchase of AM machines. Therefore, the question arises as to whether insourcing AM is profitable for spare parts production. Here, we elaborated a full factorial comparison of 2,187 instances. Following industrial applications, we considered on demand production for insourced AM, while for CM, a make-to-stock approach was used. We found that under unconstrained stock system, the insourcing of AM is not preferable due to the high costs of AM machines. Under constrained stock system, however, AM is profitable in 68.5% of the analysed instances, leading to an average saving of 46%. Furthermore, for each tested scenario, we determined the maximum order-up-to level that makes AM profitable. From this analysis, we derived a decision tree to identify under which spare parts characteristics (i.e. costs, lead time, and part reliability) and maximum order-up-to levels AM becoming profitable. This serves as a Decision Support System (DSS) to assist practitioners in selecting the best production technology.

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1. Introduction

Machine availability is increasingly important in a society where automation of plants is rising, and high customer satisfaction needs to be ensured (Dellagi et al. 2020). To avoid machine downtime, which can cause significant financial losses, especially for mass production industries with high service requirements (Muniz et al. 2021), firms usually invest heavily in spare parts, adopting large inventories (Khajavi, Partanen, and Holmström 2014). This is necessary to cope with the intermittent demands for spare parts, which are hard to forecast (Croston 1972; Syntetos and Boylan 2001), and long procurement lead times. For example, Airbus in Hamburg-Fuhlsbüttel manages more than 120,000 parts, with 80% of them required only a few times a year, leading to an inventory cost per aircraft of roughly 400,000 USD annually (Holmström et al. 2010). Given these high inventory costs associated with managing spare parts, there is a clear imperative for companies to eliminate or drastically reduce them (Ivan and Yin 2018).

This can be achieved by producing spare parts using Additive Manufacturing (AM). Thanks to the reduced lead times compared to Conventional Manufacturing (CM), AM significantly lowers inventory levels (Yadollahi and Shamsaei 2017). Inventory levels can even be reduced to zero if AM machines are insourced, allowing for on-demand production of spare parts (Peron 2024). This is particularly important in operational contexts where maintaining stock is too costly (e.g. slow-moving parts in the aircraft spare parts supply chain) and/or where space availability is limited (e.g. offshore platforms) (Westerweel et al. 2021). Indeed, these are the primary application areas where AM is currently being adopted (Fieldmade.no 2024; Junghans and Govindaraj 2024; Magazine Additive Manufacturing 2023; Naghshineh 2024), as firms are attracted by the fact that on-demand production ensures high system availability without the need for high stock levels required when using CM (Bhalla et al. 2021). Given these advantages, the AM market for spare parts and Maintenance, Repair, and Overhaul (MRO) services has experienced substantial

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growth, now making up around 50% of the total AM market (Meticulous Research 2024). In 2023, the AM market was valued at $16.14 billion and is projected to surpass $40 billion by 2028 (Report Linker 2023).

Notably, on-demand production is only feasible when AM machines are insourced. However, several obstacles limit the diffusion of AM for spare parts management. Among the different obstacles (e.g. lack of in-house AM knowledge, insufficient failure data under various loading scenarios; (Mellor, Hao, and Zhang 2014)), the major one relates to the high production costs of AM parts. These costs mainly stem from the expensive AM machines (Jiang, Kleer, and Piller 2017; Westerweel, Basten, and van Houtum 2018). As demonstrated in (Baumers et al. 2016; Mecheter, Tarlochan, and Kucukvar 2023), the cost of AM machines can account for 40-60% of the total costs.

In light of this, the decision on whether to produce spare parts using CM with a make-to-stock approach or on-demand insourcing AM machines is not straightforward. On the one hand, AM benefits from null inventory costs, but on the other hand, it is hindered by high production costs primarily due to the purchase of AM machines. To further complicate the decision, a dual-sourcing approach can also be adopted, where some spare parts are produced using AM and others using CM as suggested by Knofius et al. (2021) who demonstrated the superiority of a dual sourcing approach compared to single sourcing with either CM or AM. In light of this and as confirmed also by the literature (Cantini et al. 2024), managers and practitioners highly need a support in determining whether to produce spare parts using AM or CM. Nevertheless, as we will describe in the next section, the literature investigating whether to produce spare parts using AM or CM is limited. Most available studies fail to consider AM as an insourced option, instead considering AM spare parts as being produced by an external supplier and then shipped. Outsourcing AM production, however, is not the preferred choice for companies since, as discussed above, they are drawn to the on-demand production of spare parts (and the consequent inventory benefits) only achievable when AM is insourced. The few works that do consider insourcing AM are limited by either (i) not accounting for the cost of AM machines (which, as described above, represents the major cost factor in the final cost of AM parts), or (ii) assuming that AM and CM spare parts share the same attributes (e.g. failure rates, lead times), which does not hold true as shown in (Lolli et al. 2022b), (Cantini et al. 2024), (Sgarbossa et al. 2021), and (Westerweel et al. 2021), or (iii) neglecting the dual-sourcing approach.

This work aims to fill the literature gap by identifying the conditions under which spare parts should be produced using CM with a make-to-stock approach, and the conditions under which they should be produced on-demand with insourced AM machines. Notably, following the identified benefits of a dual-sourcing approach over a single sourcing AM/CM approach (Knofius et al. 2021), in this work we consider a dual sourcing approach where some spare parts are produced using AM and some using CM. Therefore, the research question (RQ) we aim to answer is the following:

> RQ: under a dual sourcing approach, under which conditions spare parts should be produced on-demand with insourced AM machines instead of in CM following a make-to-stock approach?

To answer this research question (RQ), we developed an optimisation model and conducted a full factorial comparison of the model by analysing 2,187 instances obtained by varying spare parts characteristics (e.g. lead times, failure rates, backorder costs). Notably, in doing so, and following the literature, we considered that AM and CM are characterised by different spare parts attributes (Cantini et al. 2024; Lolli et al. 2022a; Sgarbossa et al. 2021; Westerweel et al. 2021). Moreover, we considered both unconstrained and constrained stock systems, with the latter included to resemble applications characterised by limited stocking space where insourced AM is currently used for producing spare parts (e.g. offshore platforms by Equinor (Equinor 2022) and remote military operations (Westerweel et al. 2021)). Thus, our research question aims to understand which spare part characteristics and constrained level of the system (i.e. unconstrained or constrained stock systems) are suitable for on-demand production of spare parts using insourced printers and which are not. Given that such settings (on-demand and insourced AM spare parts production) are the most commonly used in practice (Fieldmade.no 2024; Junghans and Govindaraj 2024; Magazine Additive Manufacturing 2023) this work is expected to be highly beneficial for practitioners as it intends to guide them on the economic feasibility of insourcing AM resources from an industrial perspective. More in details, a specific tool for this purpose, namely a decision support system (DSS), has been developed.

From the results, we observed that under unconstrained stock systems AM is never the preferable option (not even in dual sourcing) due to the high costs of insourcing AM machines. However, this changes when constrained stock systems are considered. In such scenarios, AM is profitable in 68.5% of the analysed instances. We further extended our analyses to determine, for each instance considered (i.e. each combination of different spare parts characteristics), the level of stock constraint that would render AM preferable. Based on this analysis, we developed a decision tree-based Decision Support

System (DSS) to support managers and practitioners in identifying which spare parts characteristics and stock constraint levels make insourced AM on-demand production preferable over CM. This DSS can effectively address our RQ in a practical way by adapting to the specific situation encountered. Finally, we investigated the impact of future AM technological advancements and related cost reductions on this decision.

The remainder of the paper is structured as follows: Section 2 contains the literature review of available models for the management of spare parts with AM and underlines their limitations; Section 3 contains the methodology followed and includes the proposal of our mathematical model as well as the full factorial comparisons exploited for its tests, while in Section 4 our extensive experimental analysis is presented; Section 5 contains our conclusions and the agenda for further research.

2. Literature review

The management of CM spare parts can be carried out using either continuous or periodic inventory policies. However, due to their intermittent nature (Croston 1972; Hasni et al. 2019; Syntetos and Boylan 2001) periodic inventory policies are typically preferred (S. Hu et al. 2018; Zhang, Huang, and Yuan 2021). Among these, one of the most widely used inventory policies in the industry is the well-known base-stock inventory replenishment policy, also known as the order-up-to level inventory policy (Basten and van Houtum 2023; Wingerden, Tan, and Van Houtum 2019). Under this policy, stock levels are periodically reviewed and replenished to their optimised order-up-to levels (Boucherie et al. 2018). However, given the critical nature of spare parts and their long lead times, the optimised order-up-to levels often result in excessive inventory costs for industries (Heinen and Hoberg 2019). For this reason Additive Manufacturing (AM) is being explored as a means to reduce inventory costs while maintaining the high service levels essential for the strategic importance of spare parts and after-sales operations in many firms (Visnjic Kastalli and Van Looy 2013). Assessing the profitability of this transition is challenging due to the distinct attributes of AM and CM parts (Agnusdei and Del Prete 2022; Peron, Coruzzolo, et al. 2024), such as higher production costs and different failure rates. The literature has tried to provide an answer to whether spare parts should be produced in AM or CM, but as it will be highlighted below and as summarised in Table 1, some major gaps exist.

Following Holmström et al. (2010) call for quantitative research on the impact of AM on spare parts supply chains, Khajavi, Partanen, and Holmström (2014) assessed the costs associated with integrating Additive Manufacturing (AM) into the spare parts supply chain for the F-18 Super Hornet fighter jet, taking into account both current and future AM cost scenarios. This study was among the first to quantitatively explore this topic, highlighting the costs related to AM, but it did not offer a comparison with CM. This comparison was offered for the first time by Liu et al. (2014), who tried to shed light on whether spare parts should be produced in AM or CM. Focusing again on aircraft spare parts supply chains, they compared AM and CM, showing that AM should be preferred since it would reduce the inventory levels by up to 70% compared to CM. However, the validity of such results is limited by the fact that, in their comparison, Liu et al. (2014) neglected relevant cost items such as production costs. Similar studies focusing only on inventory levels and costs are those of Sirichakwal and Conner (2016) and Ghadge et al. (2018). This drawback was first overcome by Li et al. (2017), who investigated the impact of AM in the performance of a supply chain and compared two AM-based supply chains with a CM-based one, showing how AM would lead to the lowest total costs. However, the validity of the results reported by Li et al. (2017) is limited by the fact that they based their analyses only on variable costs, without considering fixed costs such as the purchasing cost of AM machines. As Li et al. (2017) themselves stated, '*if these fixed costs are taken into consideration, the AM-based supply chain might not be more cost effective than the conventional one in terms of the total cost*'.

Nevertheless, although Li et al. (2017) highlighted the importance of including fixed costs in the analysis, the literature has often neglected them. Examples of these works are (Heinen and Hoberg 2019; Khajavi, Deng, et al. 2018; Y. Knofius et al. 2021; Knofius, van der Heijden, and Zijm 2019; Mecheter et al. 2024; Westerweel, Basten, and van Houtum 2018; Zhang et al. 2019).

Worth mentioning are the papers of Knofius, van der Heijden, and Zijm (2019) and Knofius et al. (2021) which are the first to consider the possibility to use together AM and CM in a dual sourcing approach (all the previous papers considered a single sourcing approach where spare parts were produced either in CM or in AM), with CM being used for regular supply and AM for emergency supply. Their results indicated that this dual sourcing approach is always to be preferred over a single sourcing one (either AM or CM), with cost savings of more than 30%. Similar results were found recently by Roozkhosh et al. (2024), who also demonstrated that such a hybrid approach can effectively reduce costs within the supply chain.

These works, however, in addition to neglecting the fixed costs of AM machines, are also characterised by two

Table 1. Literature review analysis.

Article	Focus	Findings	Problem settings: Sourcing approach: AM/CM single	Problem settings: Sourcing approach: Dual sourcing	Problem settings: AM production: Insource	Problem settings: AM production: Outsource	Problem settings: AM machines costs: Considered	Problem settings: AM machines costs: Not considered	Problem settings: AM & CM failure rates: similar	Problem settings: AM & CM failure rates: different	Limitations and gaps
Khajavi, Partanen, and Holmström (2014)	Centralised vs Decentralised AM.	Decentralised AM is limited by the high cost of machines.	X		X		X		N/A	N/A	(1) AM supply chain not compared with CM. (2) Only identical parts are considered.
Liu et al. (2014)	Reduction of safety stock.	Up to 70% of stock reduction.	X			X		X	X		(1) Costs perspective is missing.
Sirichakwal and Conner (2016)	Influence of AM on spare parts inventory.	A reduction in holding costs has a greater impact on lowering the stock-out probability when the average demand rate for spare parts is low.	X		X			X	X		(1) AM parts less expensive than CM ones.
Li et al. (2017)	CM vs Centralised or Decentralised AM supply chain evaluating CO_2 impact.	Decentralised AM can lead to up to a 46% cost reduction.	X		X			X	X		N/A
Ghadge et al. (2018)	Impact of AM on aircraft supply chain performance.	Up to 85% reduction of mean stock.	X		X	X		X	X		N/A
Khajavi et al. (2018)	Switchover point between AM and CM varying AM production costs.	Using significantly cheaper raw materials lowers the production costs of AM.	X		X		X		N/A	N/A	(1) Parts reliability not included
Westerweel, Basten, and van Houtum (2018)	Lifecycle cost analysis to find breakeven point between CM or AM parts.	AM offers logistics savings by reducing production lead times, allowing slight trade-offs in reliability and production cost.	X			X		X	X	X	(1) CM parts with higher or equal reliability of AM ones.
Heinen and Hoberg (2019)	Switchover point between AM and CM focusing on production cost.	Up to 8% of SKUs could be produced using AM even if AM parts cost four times more than CM ones.	X			X		X	X		(1) Empirical study.
Zhang et al. (2019)	CM vs AM on demand.	AM on demand face challenges in cost competitiveness, applicable only to small parts.	X			X	X		X		N/A
Knofius, van der Heijden, and Zijm (2019)	CM vs AM for low volume spare parts.	Average cost savings of about 35% moving to AM. Dual sourcing reduces holding costs.		X		X	X		X		N/A
Li et al. (2019)	Centralised vs Decentralised vs Mixed AM.	A mixed configuration outperforms both centralised and distributed AM.	X		X		X		N/A	N/A	(1) AM not compared with CM.
Song and Zhang (2020)	CM vs pure on demand AM with insourced printer	Dual sourcing outperforms a single sourcing with CM or AM.		X	X		X		X		(1) AM only on demand. (2) Only one printer can be insourced.

Westerweel et al. (2021)	AM for remote locations.	Average annual operating costs decrease by 55% with AM.		X	X		X			X	(1) CM parts with higher reliability of AM ones.
Knofius et al. (2021)	Single sourcing (CM or AM) vs dual sourcing.	Dual sourcing outperforms both single sourcing with CM or AM.		X		X		X	X	X	(1) CM parts with higher or equal reliability of AM ones.
Sgarbossa et al. (2021)	Decision support system (DSS) to select CM or AM for spare parts management.	CM more cost-effective than AM except with limited stocks.	X			X				X	(1) Backorders are not directly proportional to waiting time. (2) Multi-part perspective is missing.
Lolli et al. (2022b)	Age based preventive maintenance with different AM options.	Low backorder costs, high failure costs, and high maintenance costs favour AM-based maintenance policies.		X		X		X		X	N/A
Cantini et al. (2024)	Decision support system (DSS) to select spare parts configuration (centralised vs decentralised vs hybrid) with CM or AM.	Hybrid configurations are the most suggested strategies by the DSS.	X			X		X		X	N/A
Mecheter et al. (2024)	Multi-period multi part investigation of AM.	AM is cost-effective for parts with high geometric complexity.	X		X		X		X		N/A
Roozkhosh et al. (2024)	Flexible multi-level supply chain.	Dual sourcing outperforms both single sourcing with CM or AM.		X		X		X	X		N/A
Lolli et al. (2022a)	CM vs pure on demand AM with insourced printer.	On demand printing is preferable over CM only with stocks constraint.		X	X					X	(1) Only one printer can be insourced. (2) Preliminary study with limited analysis.
This work	CM vs pure on demand AM with insourced printer's vs dual sourcing.	N/A		X	X		X			X	N/A

other drawbacks. First, they consider AM production to be outsourced and not insourced, which is not aligned with the current industrial use of AM. Indeed, as discussed in the previous section, the majority of industrial applications of AM involve insourced AM production (Equinor 2022; Khajavi et al. 2018), which can enable on-site and on-demand production with no inventory needs, characteristics highly valued in remote application such as offshore platforms and military missions. Then, these works are limited by another major drawback, i.e. they consider AM and CM parts to be characterised by the same failure rate (Knofius, van der Heijden, and Zijm 2019; Roozkhosh et al. 2024) or AM to be characterised by higher failure rates (Knofius et al. 2021; Westerweel, Basten, and van Houtum 2018). However, both assumptions do not hold true. Indeed, as shown by recent literature (Cantini et al. 2024; Lolli et al. 2022b; Sgarbossa et al. 2021), AM is no longer characterised by higher failure rates; on the contrary, it can achieve failure rates that are even 5-6 times lower than CM (Sgarbossa et al. 2021).

So far, however, the literature has failed to overcome such limitations jointly. As already discussed, some works consider AM spare parts characterised by lower failure rates than CM parts. This is the case with Lolli et al. (2022b), Cantini et al. (2024), and Sgarbossa et al. (2021). However, these works either considered AM to be outsourced, thus disregarding current industrial practices, or considered AM to be insourced but focused only on variable costs, hence neglecting the costs of AM machines which are definitely not negligible. Other works, by contrast, considered insourced AM including both fixed and variable costs. This is the case for Li et al. (2019) and Song and Zhang (2020). However, both of these works considered AM and CM to be characterised by the same failure rates. To the best of the authors' knowledge, there is only one work in the literature trying to overcome both limitations jointly, which is a conference paper proposed by this research team (Lolli et al. 2022b). Indeed, Lolli et al. (2022a) investigated whether spare parts should be produced using AM or CM considering (i) that AM is insourced with the corresponding fixed costs of AM machines and (ii) that AM is characterised by failure rates that are lower than those of CM. Moreover, following Knofius et al. (2021), they considered the possibility to use together AM and CM in a dual sourcing approach. However, this work, being a conference paper, has several major limitations, the most significant being that only one printer could be purchased and used and only one type of spare part was considered.

This work builds on (Lolli et al. 2022a) and overcomes its main limitations. Indeed, we consider the possibility of purchasing and using multiple printers (instead of just one) to manage a certain number of spare parts (instead of just one type) installed in a fleet of systems. In doing so, we consider that spare parts can be produced not only with an AM/CM single sourcing approach but also with a dual sourcing approach. Furthermore, we consider that AM spare parts are characterised by lower failure rates than CM parts, as current practice suggests. In this way, this work not only extends the current literature in the field of spare parts but is also the first to extensively address the topic and demonstrate relevance to practice by considering the current industrial settings adopted for AM.

3. Methodology

In this section, the methodology employed in this study is outlined. As described above, this work aims to identify, under a dual sourcing option, the conditions under which spare parts should be produced on-demand with insourced AM machines instead of in CM following a make-to-stock approach. This implies determining which characteristics of spare parts (i.e. part's reliability, lead time, backorder costs, production time, purchasing or production cost, revision period) render them suitable for being produced in AM and which not. More specifically, since industrial settings can be either constrained or unconstrained in terms of inventory levels, the goal is to study both stock systems. To do so, the first step is to develop a mathematical model that, given a certain set of spare parts, determines which spare parts should be produced in AM and which in CM in order to minimise the total relevant costs associated with the dual sourcing of CM and AM parts. In doing so, not only will the number of spare parts produced via AM be optimised, but also the number of insourced 3D printers and the order up to level of part managed with CM. This optimisation model will be described in detail in Section 3.2, and it will be preceded by the model notation in Section 3.1. Notably, given the complexity inherent in quantifying the queue at the printer a simulation nested in the optimisation model has been developed and will be presented in Section 3.3.

Once the optimisation model has been developed, a second step was necessary to answer our RQ, i.e. to develop the set of spare parts to which the mathematical model will be applied. To do so, we employed a full factorial comparison where we examined different levels for the input parameters of the mathematical model (i.e. different spare parts characteristics). In this way, we were able to identify which spare parts characteristics favour AM production and which do not, hence answering our RQ. Notably, considering that stock levels can also be constrained (as, for example, in remote locations, offshore platforms, . . .), we carried out two factorial analyses: one for unconstrained

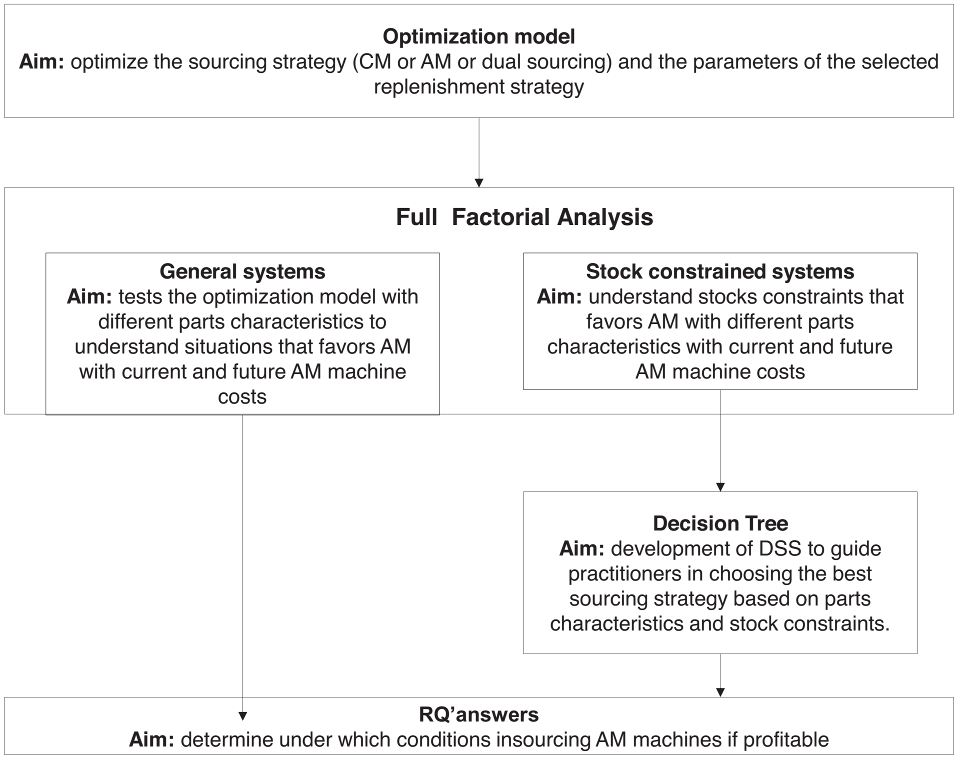

Figure 1. Framework of the followed methodology.

stock levels and one for constrained stock levels, which will be detailed in Section 3.4. Furthermore, these two full factorial analyses were repeated considering different values of printer purchasing costs to account for future situations where the cost of printers may decrease. Finally, to further assist practitioners in selecting the optimal production technology and inventory management policy for spare parts based on their stock constraints, we decided to create a Decision Support System (DSS). To do this, we started from the results of the full factorial analysis for the constrained stock levels, and we applied a machine learning approach (i.e. a decision tree algorithm). The methodology adopted for this will be described in Section 3.5. For the sake of clarity, a schematic representation of the methodologies adopted and their link to the RQ is depicted in Figure 1.

3.1. Model notation

Here, the notation used in the optimisation model will be presented, categorised into input data, parameters, decision variables and simulated ones (for more details on the meaning of simulated values, please refer to Sections 3.2. and 3.3.).

Input data

c_a	unitary purchasing cost of the CM option $\left[\frac{e}{part}\right]$
c_b	unitary backorder cost per time unit $\left[\frac{e}{part * week}\right]$
c_p	production cost of the AM option $\left[\frac{e}{part}\right]$
f	fixed weekly costs for the purchasing of a 3D printer, considered as depreciation
h	weekly holding rate $\left[\frac{1}{week}\right]$
i	production mode (options are CM or AM).
λ_i	failure rate of the spare part made with production mode-i $\left[\frac{part}{weeks}\right]$
LT	replenishment lead time of the CM option
$MTTF_i$	mean time to failure of the spare part made with production mode-i [*weeks*]
N	total number of spare parts installed
S_{max}	maximum order-up-to level for CM option in stocks constrained systems
T	review period
t_{prod}	production time of the AM option [*weeks*]

Parameters

CA	purchasing cost for CM parts $\left[\frac{e}{week}\right]$
CB_{AM}	backorder cost for AM parts $\left[\frac{e}{week}\right]$
CB_{CM}	backorder cost for CM parts $\left[\frac{e}{week}\right]$
CH	inventory cost $\left[\frac{e}{week}\right]$
CS	weekly cost for the purchasing of a 3D printer
C_{sav}	difference between the cost for the management of the parts using only CM parts with the stock constraint that favours AM versus manage them with AM parts printed on demand
S_{pass}	refers to the specific order-up-to level where the transition from traditional CM to AM becomes convenient for instances where the insourcing of a printer was not preferred without introducing stocks constraints

Decision variables

n_{AM}	number of spare parts produced on demand via AM, variable to be optimised. Thus, $N - n_{AM}$ represent the number of spare parts produced with CM managed with stocks.
m	number of insourced 3D printers, variable to be optimised
S	order-up-to level for CM option, variable to be optimised

Simulated variables

$t_{FM,n_{AM},m}$	expected waiting time at the printer for producing n_{AM} parts via AM using m-printers

3.2. Mathematical model

As discussed above, the focus of this work is on a dual sourcing strategy for spare parts management, involving CM and AM. CM spare parts are purchased from an external supplier following a make-to-stock approach, with optimised stock levels managed using a periodic inventory policy. AM spare parts, on the other hand, are produced on demand through insourced AM machine(s). As commonly assumed in the literature (Babai et al. 2021; Sgarbossa et al. 2021; Topan and Bayindir 2012), spare parts are characterised by Poisson distributed demand. In the case of AM spare parts, we assume that this Poisson-distributed spare parts' arrival is served through deterministic production time, i.e. a M/D/c queue system is considered. The decision variables that will be optimised by the model are the fraction of spare parts produced via AM (n_{AM}), the number of insourced 3D printers (m), and the order up to level of CM parts (S). Before presenting the mathematical model, the underlying hypotheses will be discussed and justified, drawing on relevant literature.

3.2.1. Model hypotheses

The hypotheses underlying our model are listed below, with relevant literature provided to support each:

1. For both AM and CM parts, the failures are distributed as Poisson processes. This is a common assumption for spare parts (Babai et al. 2021; Sgarbossa et al. 2021; Topan and Bayindir 2012).
2. The model aims to manage a spare part that is installed on a fleet of N-systems. This approach aligns well with industrial applications, such as managing a fleet of N radar systems as demonstrated by Knofius, van der Heijden, and Zijm (2019). However, when referring more generally to a fleet of systems, as discussed in Knofius et al. (2021), it can also be applied to other industrial contexts, including fleets of N aircraft, tractors, and production machines.
3. Failure rates depend only on the production technology adopted (i.e. AM or CM); for each technology adopted, we consider that parts' failure rates are the same in each system of the fleet. This is a common assumption in literature (Knofius et al. 2021; Knofius, van der Heijden, and Zijm 2019; Sgarbossa et al. 2021; Westerweel et al. 2021).
4. Each system of the fleet has its own inventory for CM parts, but all systems have the same optimised order-up-to level and review period. This assumption of local inventory follows Song and Zhang (2020).
5. The review period of CM parts is taken as an input for the problem, but it is tested on different levels. This approach simplified the optimisation problem and aligned well with industrial practice, where only fixed review periods are feasible (e.g. reviewing the inventory every week or at multiple intervals). The same assumption has been made by Sgarbossa et al. (2021).
6. AM is adopted on-demand only, i.e. no AM parts are kept in stock. As previously stated, on demand printing represents the primary domains where AM is currently utilised (Fieldmade.no 2024; Junghans and Govindaraj 2024; Magazine Additive Manufacturing 2023). For this reason, others work available in literature made the same assumption (Song and Zhang 2020; Westerweel et al. 2021).
7. The 3D printer can print all the different parts and multiple equal printers can be insourced. This assumption is particularly valid for small spare parts, as noted in this context. It is also a common assumption in the related literature (Li et al. 2019; Song and Zhang 2020; Westerweel et al. 2021).

3.2.2. . Mathematical model formulation

As introduced in the notation, the decision variables of the model are the fraction of spare parts produced via AM (n_{AM}), the number of insourced 3D printers (m) and the order up to level of part managed with CM (S). The objective function aims to minimise the total costs associated with the dual sourcing of conventional manufacturing (CM) and additive manufacturing (AM) parts, as outlined in Equation 1. Specifically, the total cost associated with the dual sourcing approach derives from the sum of the purchasing cost of the spare parts sourced in CM (CA), production cost of printed parts (CP), backorder costs for CM parts (CB_{CM}) and of AM parts (CB_{AM}), holding cost of CM parts (CH) and of purchasing cost for the printers (CS). The different costs are reported in Equations 2–7:

$$o.f.: min\ Ctot = CA + CP + CB_{CM} + CB_{AM} + CH + CS \tag{1}$$

$$CA = (N - n_{AM}) \cdot c_a \cdot \lambda_{CM} \tag{2}$$

$$CP = n_{AM} \cdot c_p \cdot \lambda_{AM} \tag{3}$$

$$CB_{AM} = n_{AM} \cdot c_b \cdot t_{FM,n_{AM},m} \cdot \lambda_{AM} \tag{4}$$

$$CB_{CM} = (N - n_{AM}) \cdot \sum_{y=S}^{\infty}(y - S) \cdot P_{\lambda_{CM},T+LT,y} \cdot c_b \cdot \left(\int_0^{T+LT} \frac{\lambda_{CM}^y \cdot t^{y-1} \cdot e^{-\lambda_{CM}t}}{(y-1)!} \cdot (T + LT - t)dt\right) \tag{5}$$

$$CH = \sum_{y=0}^{S-1} (S - y) \cdot P_{\lambda_{CM},T+LT,y} \cdot h \cdot c_a \tag{6}$$

$$CS = m \cdot f \tag{7}$$

Notably, the optimisation model is constrained by equations 8÷12: failures of CM parts follow the probability mass function of a Poisson process (8), parts can be printed if and only if at least one printer is purchased (9); a maximum of N parts can be printed (10); the maximum order-up-to level may be constrained (11); and all the control variables must be integers (12).

s.t.

$$P_{\lambda_{CM},T+LT,y} = \frac{(\lambda_{CM}(T + LT))^y \cdot e^{-\lambda_{CM}(T+LT)}}{y!} \tag{8}$$

$$n_{AM} \le M \cdot m \tag{9}$$

$$0 \le n_{AM} \le N \tag{10}$$

$$0 \le S \le S_{max} \tag{11}$$

$$n_{AM}, S, m \in N \tag{12}$$

As it can be seen, the mathematical model is a mixed integer non-linear problem (MINLP). To solve these kinds of problems, metaheuristic optimizations are adopted (Sahinidis 2019). Following the literature that reports genetic algorithms are among the most diffuse and accurate metaheuristics (Abdel-Basset, Abdel-Fatah, and Sangaiah 2018), in this work we have adopted a genetic algorithm named MI-LXPM (Deep et al. 2009) which is coded in MATLAB® optimisation tool box. The optimisation was carried out by imposing a function tolerance of 1e-6. In this way the algorithm halts if the average relative change in the best fitness value over a specified number of generations (50) is less than or equal to 1e-6.

Notably, as visible from Equation 4, in order to calculate the backorder costs for AM parts, the waiting time at the printer for producing n_{AM}-parts using m-printers must be evaluated ($t_{FM,n_{AM,m}}$). However, this evaluation requires modelling an M/D/c queue that is not easy to solve mathematically (Franx 2001). Therefore, to overcome this issue, we have nested a simulation within the optimisation model, used just to calculate the parameter $t_{FM,n_{AM,m}}$. This means that for each possible solution generated by the genetic algorithm, a simulation is performed to assess the waiting time at the printer, based on the number of parts being printed and the number of insourced printers. In this way, all relevant costs for each tested solution are accounted for.

3.3. Simulation nested in the optimisation model

Here, the simulation nested in the optimisation model, which is used just to evaluate the expected waiting time at the printer for producing n_{AM} parts via AM using m-printers, will be presented. Below is the pseudo-code of the implemented simulation:

```
Inputs: (n_AM; λ_AM;m;t_prod)
Initialize:   (λ_AMtot = λ_AM * n_AM;   q_times = [];   wating_time = 0;
arrival_time = [], n_repetition = 100.000)
for i in range(0, n_repetition):
    Create random arrival time of parts based on λ_AMtot
    Populate arrival_time
for i in range(0,m):
    Inizialize the q_times at zero for each printer
for i in range (0, n_repetition)
    Find the k-printer with the minimum queue time
    Check if the k-printer can start processing the part
    wating_time = wating_time + q_times[k]
    q_times[k] = q_times[k]+t_prod
t_FM,n_AM,m = wating_time/n_AM
Output: (t_FM,n_AM,m)
```

As shown, the simulation takes the following as input: the number of parts to be printed, their failure rate, the number of available printers, and the time required to print one part. Next, the variables used in the simulation are initialised, along with the number of randomly generated Poisson-distributed arrivals, which is set to 100,000.

The average waiting time for the parts is then calculated by identifying the printer with the shortest waiting time and assigning the part to that printer. The output provides the expected waiting time at the printer, which is necessary to evaluate Equation (4).

3.4. Full factorial comparisons

To analyse the conditions that favour AM over CM, we employed a full factorial comparison. This well-established method is widely used for parametric analysis in optimisation models and has been frequently applied in spare parts management (Cantini et al. 2024; Peron, Agnusdei, et al. 2024; Sgarbossa et al. 2021). Our full factorial comparison is divided into two analyses: the first focuses on general systems, i.e. unconstrained stock systems, as detailed in Section 3.4.1, while the subsequent analysis examines special systems, i.e. stock-constrained systems, as presented in Section 3.4.2.

3.4.1. Full factorial comparison for general systems

In our first full factorial comparison, we examined different levels of production times for AM parts (t_{prod}), number of spare parts installed (N), lead times (LT), and review periods (T) for CM parts. Additionally, we tested different backorder costs (c_b), purchasing costs (c_a) for CM parts, and production costs (c_p) for AM parts. By varying the model parameters on different levels exploiting real word data as reported in Table 2, we tested a total of 2,187 instances. In this comparison, while failure rates (λ_{CM} and λ_{AM}) were varied, the ratio between them remained constant following the material science approach of Sgarbossa et al. (2021) (see Table 3).

Moreover, we assumed a fixed weekly holding rate of 0.0058 $\left[\frac{1}{week}\right]$ (Azzi et al. 2014) and a weekly cost for the printer of 769 $\left[\frac{e}{week}\right]$ based on a purchasing cost of 200,000 € amortised in 5 years, each one with 52 working weeks. This purchasing cost refers to a printer capable of producing small parts via Selective Laser Melting and Polishing (SLM + P), as Sgarbossa et al. (2021) identified SLM with polishing as the optimal AM technology combination for small parts. For a more in-depth discussion on part sizes, geometry complexity, and reliability parameters, readers can refer to Sgarbossa et al. (2021). Conversely, the CM part is produced via Cast and Polishing (C + P). This full factorial comparison was further extended by incorporating different levels of printer purchasing cost reduction (from 10% to 90%) to account for potential future technological advancements, leading to a total of 19, 683 instances tested.

Table 2. Full factorial comparison.

Model inputs	Tested values			Reference from which one or more of the tested values have been selected.
$t_{prod}[week]$	0.1	0.2	0.3	Peron et al. (2022)
N	10	80	150	Westerweel, Basten, and van Houtum (2018)
$LTandT[week]$	4	14	24	Knofius et al. (2021)
$MTTFlevels$	1	2	3	Sgarbossa et al. (2021)
$c_p\left[\frac{e}{part}\right]$	100	175	250	Cantini et al. (2024)
$c_b\left[\frac{e}{part * week}\right]$	2000	26000	50000	Sgarbossa et al. (2021)
$c_a\left[\frac{e}{part}\right]$	30	40	50	Peron et al. (2022)

Table 3. *MTTF* levels in the full factorial comparison.

MTTF levels	1	2	3
$\lambda_{AM}\left[\frac{part}{weeks}\right]$	0.0055	0.0022	0.0014
$\lambda_{CM}\left[\frac{part}{weeks}\right]$	0.0385	0.01538	0.00961

3.4.2. Stocks constrained full factorial comparison

To understand how the profitability of on-demand printing changes when considering its most relevant current industrial practice i.e. AM for special locations with limited stocking space (Equinor 2022; Westerweel et al. 2021), a subsequent constrained full factorial comparison was conducted, building on the previous results. Specifically, for each instance in the unconstrained full factorial comparison where AM was not advantageous, a constrained full factorial comparison was carried out. In this analysis, the maximum order up to level of CM parts (S_{max}) was incrementally constrained until AM became viable. This threshold value of the order-up-to level, which may reach the value of 1, is called S_{pass}. The constrained full factorial comparison was further evaluated with different levels of printer purchasing cost reductions, as this cost has been identified as the primary barrier to managing parts through AM.

3.5. Decision Support System (DSS) construction

A decision tree is a graphical tool well-suited for aiding the decision-making process by clearly identifying areas of advantage. Given a set of attributes (such as spare parts demand, backorder costs, purchasing costs, lead time, etc.), it suggests the optimal solution, in this case, the best sourcing option. In other words, it helps easily and intuitively determine under which combination of spare parts characteristics (e.g. demand, backorder costs, purchasing costs, lead time) AM is the preferable sourcing choice (Cantini et al. 2024). Because of this intuitive nature, we considered the decision tree to be the ideal tool for our objective: further refining the insights gained from the previous full factorial comparisons to address our research question and provide practical guidance for choosing insourced AM for on-demand spare parts production.

To achieve this, we trained a classification tree using the CART algorithm (Loh 2004) in MATLAB®. The tree was trained on the results from the stocks constrained full factorial comparison. This allows practitioners to easily determine whether to choose CM or AM based on specific part characteristics and the stock constraints relevant to their system. More specifically, the decision tree predicts which stock constraints make AM a more advantageous choice than CM, taking into account the varied part's characteristics as reported in Section 3.4.

4. Results

In the following, we elaborate on whether it is profitable to produce spare parts in AM (and if so, which) or not considering general unconstrained stock systems with current and future AM costs (Section 4.1) and constrained stock systems with current and future AM costs (Section 4.2). Additionally, we present the Decision Support System (DSS) developed to assist practitioners in the insourcing of AM for constrained stock systems (Section 4.3).

4.1. General systems with insourced AM for on-demand production

This section presents our results on general systems. Specifically, Section 4.1.1 reports the results related to general systems with current AM costs, while Section 4.1.2 covers those with future AM costs.

4.1.1. General systems with current AM costs

As previously stated, our model has been tested on 2,187 instances obtained by varying the model parameters in a full factorial comparison exploiting real word data (see Table 2 and Table 3) considering general unconstrained stocks systems. The results of this first analysis are reported in Table 4.

As shown in Table 4, the results from our analysis exhibit a wide range of values, reflecting the variability in the tested parameters. Despite this variation, a consistent pattern emerges in all tested cases: the number of spare parts produced via AM and the number of insourced 3D printers are both zero. This suggests that, under current cost conditions, insourcing a 3D printer and adopting a pure on-demand production strategy for spare parts is not economically viable. We found a mean cost of 107.48 $\left[\frac{e}{week}\right]$ for the management of the spare parts with CM which is up to seven times lower than the weekly purchasing cost for the printer. In fact, even the highest cost for CM spare parts management was only 62.8% of the weekly printer cost. Therefore, we conducted further analysis by reducing the printer's cost.

Table 4. Results of the full factorial comparison.

Parameter	Value
C_{max}: maximum cost $\left[\frac{e}{week}\right]$.	482.95
C_{mean}: mean cost $\left[\frac{e}{week}\right]$.	107.48
C_{min}: minimum cost $\left[\frac{e}{week}\right]$.	4.23
σ_C: cost standard deviation $\left[\frac{e}{week}\right]$.	106.41
S_{max}: maximum order up to level	7
S_{mean}: mean order up to level	3.43
S_{min} : minimum order up to level	1
σ_S: standard deviation of order-up-to level	1.49
m_{max}: maximum number of insourced printers	0
m_{mean}: mean number of insourced printers	0
m_{min}: minimum number of insourced printers	0
σ_m: standard deviation of insourced printers	0
${\frac{n_{AM}}{N}}_{max}$: maximum fraction of parts printed	0
${\frac{n_{AM}}{N}}_{mean}$: mean fraction of parts printed	0
${\frac{n_{AM}}{N}}_{min}$: minimum fraction of parts printed	0
$\sigma_{\frac{n_{AM}}{N}}$: standard deviation of fraction of parts printed	0

4.1.2. General systems with future AM costs

In this section, we re-evaluated each instance with AM machine cost reductions ranging from 10% to 90%. However, we found that AM becomes cost-effective only when the purchasing cost of the printer is reduced by at least 70%. Figure 2 reports the maximum percentage saving, the mean percentage saving and the percentage of instances where AM is convenient with purchasing cost reduction of 70-80-90%. With a cost reduction of 70%, only 0.46% of instances make AM convenient. At the same time, in these few instances, AM guarantees a mean percentage saving of 13.67% and all the parts are printed. With a cost reduction for the purchasing of the printer of 80%, the printer is purchased and guarantees a mean percentage saving of 16.39% in 2.47% of instances, printing all the parts. Lastly, with a reduction of 90% for the purchasing of the printer, insourcing 3D printer is beneficial in 7.82% of instances with a mean percentage saving of 20.9% and a maximum percentage saving of 54.54%, printing all the parts. Thus, when the printer is insourced is exploited to print all the parts, meaning that a dual

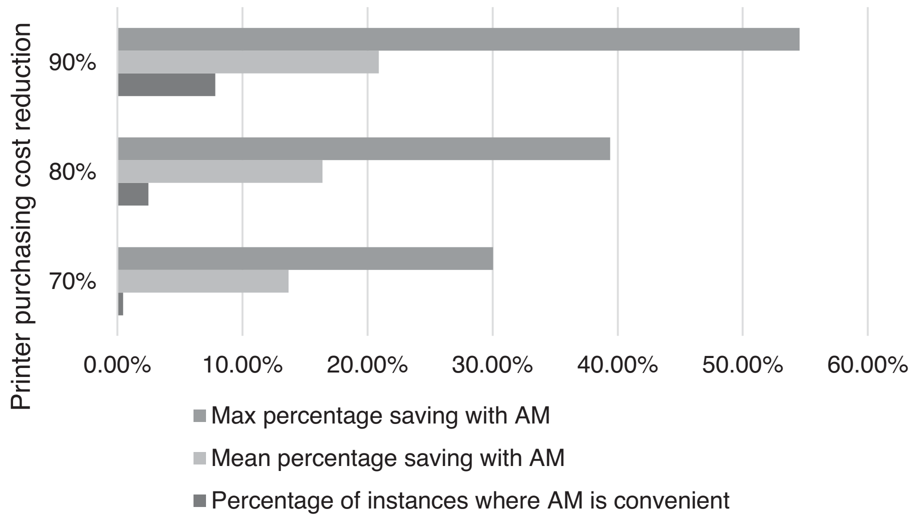

Figure 2. Maximum percentage saving, mean percentage saving and percentage of instances where AM is convenient with printer's purchasing cost reduction of 70-80-90%.

Table 5. Results analysis with purchasing cost reduction of the printer of 90%.

Parameter	Mean value in the full factorial comparison	Mean value in instances where AM is convenient	Δ%	Standard deviation in the full factorial comparison	Standard deviation in instances where AM is convenient	Δ%
$t_{prod}[week]$	0.2	0.11	−45.00%	0.08	0.03	−62.50%
N	80	83.68	4.60%	57.16	56.44	−1.26%
$LTandT[week]$	14	17.27	23.36%	8.16	7.51	−7.97%
$MTTFlevels$	2	2.08	4.00%	0.81	0.79	−2.47%
$c_p\left[\frac{e}{part}\right]$	175	148.5	−15.14%	61.25	56.05	−8.49%
$c_b\left[\frac{e}{part*week}\right]$	26'000	2000	−92.31%	19'600	0	−100.00%
$c_a\left[\frac{e}{part}\right]$	40	44.4	11.00%	8.16	6.9	−15.44%

sourcing approach is not economically convenient when the printer is purchased. This contrasts with the results available in Knofius et al. (2021), which, however, did not account for the printer being insourced, and therefore did not consider the related costs.

To identify the situations that favour the insourcing of a 3D printer with a 90% reduction in printer costs, Table 5 presents the mean values of the varied parameters across all full factorial comparisons, alongside the mean values for the instances where AM is profitable. As shown in the table, the only parameter that remains unchanged in the profitable AM instances is the backorder cost, which is consistently fixed at its lowest level. This is because a print-on-demand approach is subject to a fixed backorder time, making it less advantageous compared to a stocking policy, which guards against high backorder costs by maintaining higher inventory levels. However, as we will demonstrate, this behaviour changes when constraints on stock levels are introduced to the stocking policy. Regarding the other parameters, as visible from the table, lower production time of AM parts favours the insourcing of a printer, along with high lead times of CM parts and low printing cost for AM parts.

These results can be summarised as follows:

- The insourcing of a printer is not suitable for on-demand printing given the current purchasing costs. In fact, the weekly cost for the printer is up to seven times higher than the average weekly cost for the spare parts management with CM.
- The insourcing of a printer is not viable until the purchasing cost is reduced by at least 70%, a reduction that is not realistically achievable in the short term.
- With a significant purchasing cost reduction of the printer (90%) situations that favour the insourcing of printers are characterised by low backorder cost and high lead time of CM parts.

If a significant reduction in purchasing cost is achieved in the future, the impact of AM on general systems will not be negligible. In fact, with a reduction of 70%, the insourcing of the printer guarantees a mean percentage saving of 13.6% to 20.9% with a 90% cost reduction. However, such high-cost reductions are unlikely to occur in the near future (Thomas and Gilbert 2014).

4.2. Constrained stock systems with insourced AM for on-demand production

In this section, we investigate the profitability of on-demand AM production for spare parts in stocks constrained systems. Specifically, Section 4.2.1 presents the results using current AM costs, while Section 4.2.2 focuses on those considering future cost reduction.

4.2.1. Constrained stock systems analysis with current AM costs

Given the previous results for general systems presented in Section 4.1, we extended the analysis considering systems with constrained stock capacity as detailed in Section 3.4.2. Specifically, we expanded the analysis by reducing for each instance the optimal order-up-to levels of the CM option found in the previous analysis until the convenience of AM is verified; this threshold value of the order-up-to level is called S_{pass}. We also calculated the difference between the cost for managing the parts using only the CM options in a constrained system versus that arising using AM; this difference is named C_{sav}, while $C_{sav\%}$ indicates its percentage value. Note that AM can be still not profitable with $S_{max} = 1$.

We found that in 68.58% of instances over the 2,187 tested, constraining the order-up-to level leads to a convenience for AM. This result reinforces the importance of AM under special conditions such as remote locations. In Table 6, we report the maximum C_{sav} and $C_{sav\%}$ as well as their mean value and standard deviation; we also report these statistics for S_{pass}. It should be noted that for the remaining instances, i.e. the instances where AM is not convenient from an economic point of view, S_{pass}, C_{sav} and $C_{sav\%}$ are null, but are included in all the analysis to understand in which situations AM is not profitable even under constrained stock systems. However, for the calculation of $C_{sav\,min}$, $C_{sav\,min\%}$, , $S_{pass_{min}}$ and m_{min} zero values have been ignored.

As shown in Table 6, constraining the maximum order-up-to level favours the on-demand printing approach with insourced printers. We observed a mean saving of 7,962.9 $\left[\frac{e}{week}\right]$ across the 2,187 instances. This saving reflects the significant backorder costs incurred when the maximum order-up-to level of the CM system is constrained, leading to inadequate service levels. This is exacerbated within instances where backorder cost is at its highest level, i.e. 50,000 $\left[\frac{e}{part*week}\right]$. In particular, the maximum saving is achieved when $N = 150$, $c_a = 50$ $\left[\frac{e}{part}\right]$, $c_b = 50{,}000$ $\left[\frac{e}{part*week}\right]$, $(\lambda_{CM}, \lambda_{AM}) = (0.0385;$ $0.0055)$ and $LTandT = 14$ $[week]$. Table 6 also reveals that printer insourcing results in a mean percentage saving of 46.01%, peaking at 96.70% in constrained stock systems. This finding underscores the significant positive impact of AM across all tested instances, even those where insourcing may not be preferable, highlighting its comprehensive benefits. However, focusing only on instances where AM is profitable increases the mean percentage saving to 67.39%, with a reduced standard deviation of 24.78% compared to 37.31%. As part of further analysis, we investigated the distributions of S_{pass} values (see Figure 3) excluding 31.41% of instances where insourcing is not favourable.

Table 6. Results of the full factorial analysis with constrained order up to level.

Parameter	Value
$C_{sav\,max}$: maximum saving $\left[\frac{e}{week}\right]$.	80,320.1
$C_{sav\,mean}$: mean saving $\left[\frac{e}{week}\right]$.	7,962.9
$C_{sav\,min}$: minimum saving $\left[\frac{e}{week}\right]$.	1.781
$\sigma_{C_{sav}}$: savings standard deviation $\left[\frac{e}{week}\right]$.	14,817.3
$C_{sav\%max}$: maximum percentage saving.	96.70%
$C_{sav\%mean}$: mean percentage saving.	46.01%
$C_{sav\%min}$: minimum percentage saving.	3.94 E-4
$\sigma_{C_{sav\%}}$: percentage savings standard deviation.	37.31%
$S_{pass\,max}$: *maximum order-up-to level that favours AM*	4
$S_{pass\,mean}$: *mean order-up-to level that favours AM*	1.03
$S_{pass\,min}$: *minimum order-up-to level that favours*	1
$\sigma_{S_{pass}}$: standard deviation of S_{pass}	0.926
m_{max}: maximum number of insourced printers	2
m_{mean}: mean number of insourced printers	0.71
m_{min}: minimum number of insourced printers	1
σ_m: standard deviation of insourced printers	0.51
$\frac{n_{AM}}{N}_{max}$: maximum fraction of parts printed	100%
$\frac{n_{AM}}{N}_{mean}$: mean fraction of parts printed	100%
$\frac{n_{AM}}{N}_{min}$: minimum fraction of parts printed	100%
$\sigma_{\frac{n_{AM}}{N}}$: standard deviation of fraction of parts printed	0

Figure 3 clearly illustrates that in most cases where incorporating 3D printer insourcing becomes economically beneficial within a stock-constrained system, the maximum order-up-to level (S_{max}) must be restricted to just 1. Specifically, 59.73% of instances where AM is advantageous can be attributed to a tight limitation on S_{max}, set at 1. In other scenarios, 18.66% of the time, it is found that AM is cost-effective with an S_{max} of 2, while in 10.8% of cases, profitability is achieved with a stock constraint of 3 or 4 parts. Notably, only 10.8% of instances require an S_{max} of 4 parts to make AM profitable, which is close to the mean order-up-to level found in the initial analysis, averaging at 3.43. In these cases, the constraint on S_{max} favouring AM is significantly less stringent. Additionally, a calculation was conducted to determine the difference between the initially

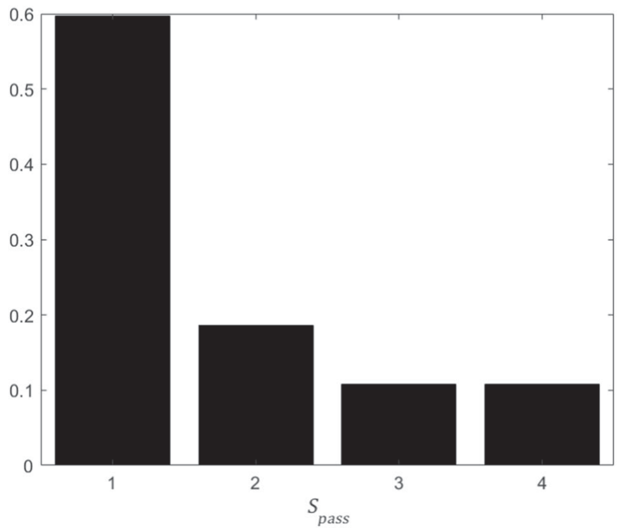

Figure 3. Bar chart of the distribution of the number of S_{pass}..

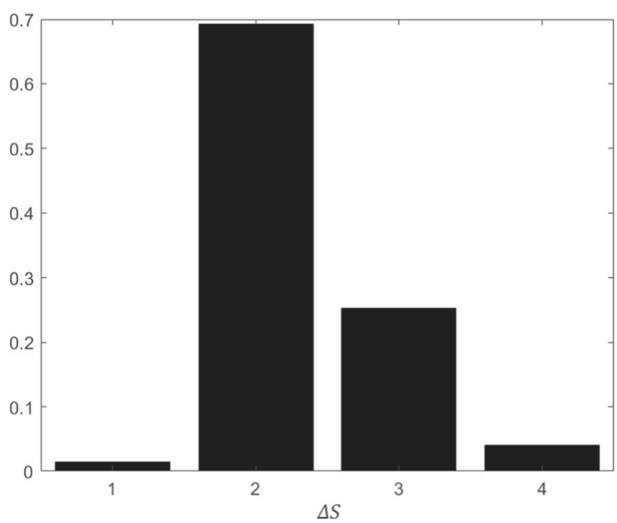

Figure 4. Bar chart of the distribution of the difference between order up to levels that favors AM and unconstrained optimized order up to level (ΔS).

optimised order-up-to level under unconstrained conditions and S_{pass}, denoted as ΔS, representing the order-up-to level where insourcing of 3D printers becomes advantageous. The outcomes of this calculation are presented in Figure 4. It is remarkable that in the majority of examined instances (70.74%), only a slight reduction in the optimised order-up-to level by 1 (1.47%) and 2 (69.27%) is necessary to make the insourcing of 3D printers preferable. This highlights that even with relatively modest constraints compared to the base case, where spare parts are managed through CM, AM can emerge as a favourable option.

Further insights from Table 6 indicate a wide distribution of savings but low variability in the number

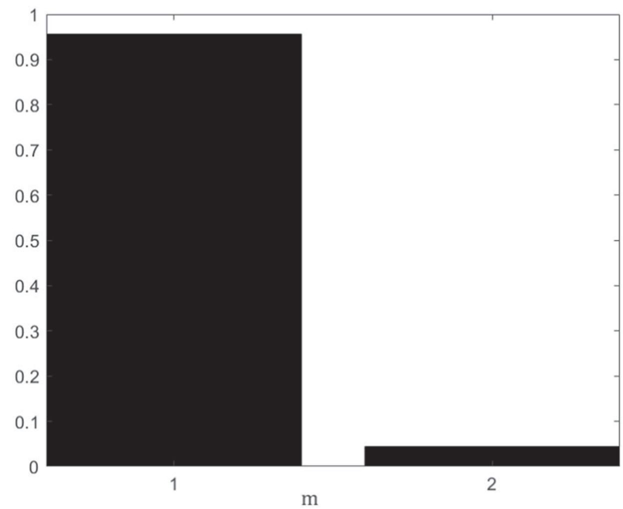

Figure 5. Bar chart of the distribution of the number of insourced printers (m).

of insourced printers. On average, 0.70 printers were insourced, with a standard deviation of 0.51. This suggests that in most scenarios, insourcing just one printer is sufficient to manage all parts effectively. To provide a better understanding of the distribution of insourced printers, Figure 5 presents a bar chart depicting the frequency of its values. Instances where insourcing remained unprofitable are excluded from the chart.

The bar chart presented in Figure 5 illustrates that, in most instances where insourcing becomes favourable, particularly in 95.5% of cases under a stock-constrained system, only one printer is required. For the remaining 4.5% of instances, two printers are necessary.

An interesting finding concerns the number of parts to be printed. In fact, the mathematical model optimised not only the number of printers to be insourced but also the fraction of parts to be printed. However, here in all 68.58% of instances where AM is convenient, 100% of parts are printed. Therefore, if the investment in printers is made, it is beneficial to print all parts rather than just a fraction. This result contrasts with current literature where a dual sourcing with AM is preferred over a single sourcing (Knofius et al. 2021). However, this difference is justified by the fact that previous research did not consider an insourced printer with its associated purchasing cost as it accounted for un-capacitated AM equipment. Conversely, printing all the parts is required to benefit from the equipment investment in insourcing scenarios.

We can summarise the main findings of this analysis as follows:

- Constrained stock systems favour AM adoption in 68.5% of the instances tested. In all these instances, it is found to be economically advantageous to print 100%

of the parts, indicating that once the investment in the printer is made, it makes sense to use it for all parts rather than just for a fraction of them.

- The insourcing of 3D printers under constrained stock systems results in a mean percentage cost saving of 46.01%, with a peak saving of 96.71%. This finding highlights the feasibility and economic advantages of on-demand spare part production in these particular scenarios.
- In 59.73% of the cases where AM is found to be economically viable, this is primarily due to a very tight constraint on the maximum order-up-to level (S_{max}), which is set to 1. Moreover, in 94.47% of the tested instances, reducing the order-up-to level to 2 or 3 parts is sufficient to make the insourcing of 3D printers economically favourable.
- Most cases where AM is profitable under constrained stock systems require only 1 (95.5%) or 2 (4.5%) insourced printers, indicating that in most instances one printer can sustain the spare part production.

4.2.2. Constrained stock systems with AM machines cost reduction

To assess the impact of future technology cost reductions on the insourcing of AM in constrained systems, we re-evaluated the effectiveness of AM for on-demand production under reduced printer purchasing costs of 5%, 10%, and 15%, realistic values for the near future. In particular, Figure 6 reports the mean percentage variations respect to the base case analysed in Section 4.2.1 including: the percentage of instances where AM is more profitable ($\Delta\%AM$); the mean S_{pass} ($\Delta S_{pass_{mean}}$); the mean saving provided by AM respect to CM in constrained stock systems ($\Delta C_{savmean}$); the mean number of insourced printers (Δm_{mean}); the mean cost of AM management when AM is profitable constraining the stocks (ΔCAM_{mean}).

As visible from Figure 6, reducing the printer purchasing cost has a limited impact on the percentage of instances where AM is advantageous, increasing by only 0.80% when reducing the purchasing cost by 15%. This suggests that the primary drivers making AM profitable in these instances are stock constraints and the part's characteristics. Specifically, the most influential parameters are $MTTF$ and LT, alongside backorder cost. Simultaneously, decreasing the cost for the purchasing of the printer results in higher S_{pass}, up to 10.68% higher on average compared to the base case. This outcome was expected, indicating that lowering printer costs reduces the stock constraints favouring AM. While the mean percentage saving using AM remains quite stable with a maximum improvement of 1.33%, the mean number of insourced printers increases up to 6.21% when the purchasing cost of the printer is reduced of 15%. Lastly, the mean cost for the spare parts management with AM decreases of about 5% while decreasing the printer cost by 15%.

4.3. Decision Support System (DSS) development for constrained stock systems

To assist managers and practitioners in choosing between CM or on-demand production with AM for spare parts management, we developed a DSS based on a decision tree, as detailed in Section 3.5. Specifically, we trained a classification tree with S_{pass} as the variable to be predicted and the varied parameters from the full factorial comparison as input variables. Thus, the tree is able to

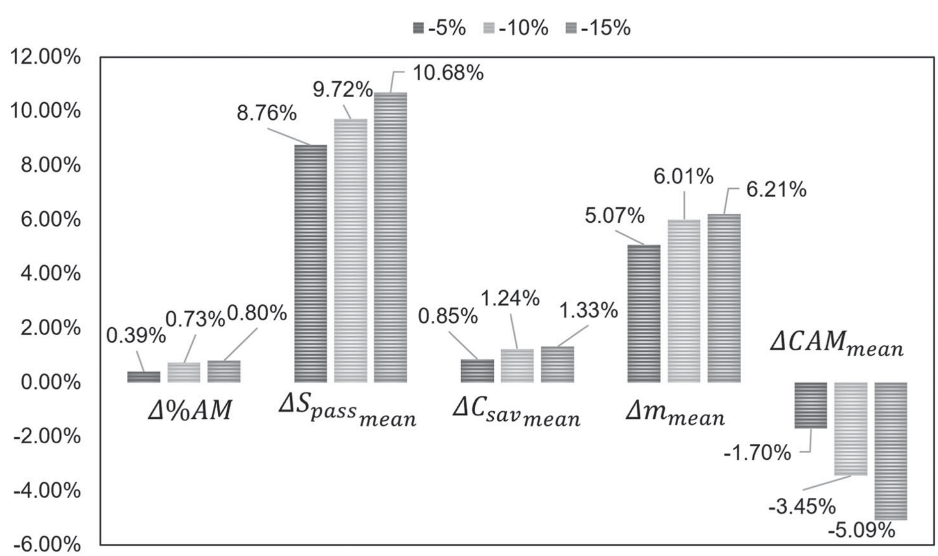

Figure 6. $\Delta\%AM$, $\Delta S_{pass_{mean}}$, $C_{sav\,mean}$, Δm_{mean} ΔCAM_{mean} reducing the printer purchasing cost of 5-10-15%.

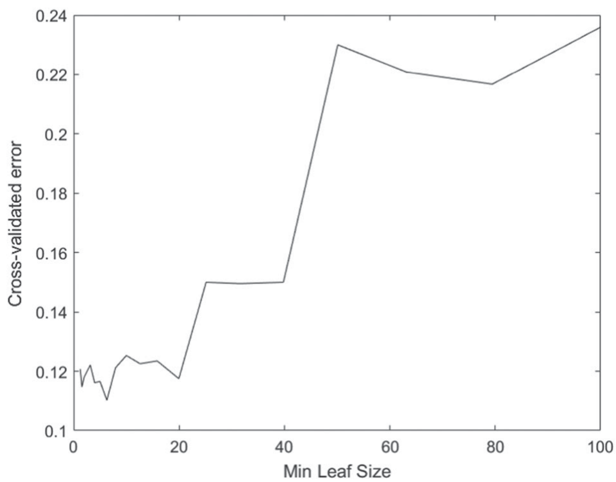

Figure 7. Cross validated error changing minimum leaf size.

predict how much constrained in terms of stock capacity the system must be to make on-demand printing advantageous. In order to control the tree depth, we calculated the cross validated loss by changing the number of minimum instances in each leaf, i.e. leaf size generating an exponentially spaced set of values from 1 to 100. The results are shown in Figure 7.

Figure 7 demonstrates that the optimal leaf size for building the decision tree is approximately eight instances per item, corresponding to a loss of 0.11. However, having fewer than ten instances per leaf can lead to an overly specialised tree. To mitigate this issue, we set the minimum leaf size to twenty, as its loss is close to 0.12 and similar to that of a minimum size of eight. Despite this adjustment, the resultant tree is quite extensive, potentially reducing its practical usability and readability. To address this concern, we pruned the tree by removing half of its levels. The pruned tree (Figure 8), which shows the suggested S_{pass} based on parameters' structure, maintains a reasonable depth and ensures a high level of usability and interpretability. For each leaf of the tree, we calculated:

- p = percentage of instances that reach the leaf.
- e = percentage of misclassification in the leaf.
- c = percentage mean cost for the misclassification in the leaf. The misclassification cost was calculated in two different ways. If the predicted S_{pass} was higher than the real one, we calculated the difference between initial solution without AM and the one using the suggested S_{pass}. Otherwise, if the predicted S_{pass} was lower than the real one, we calculated the differences between the two solutions with AM.
- r = percentage mean saving for the correct classifications in the leaf.

The decision trees highlighted the crucial role of lead time (LT) and review period (T) in decision-making.

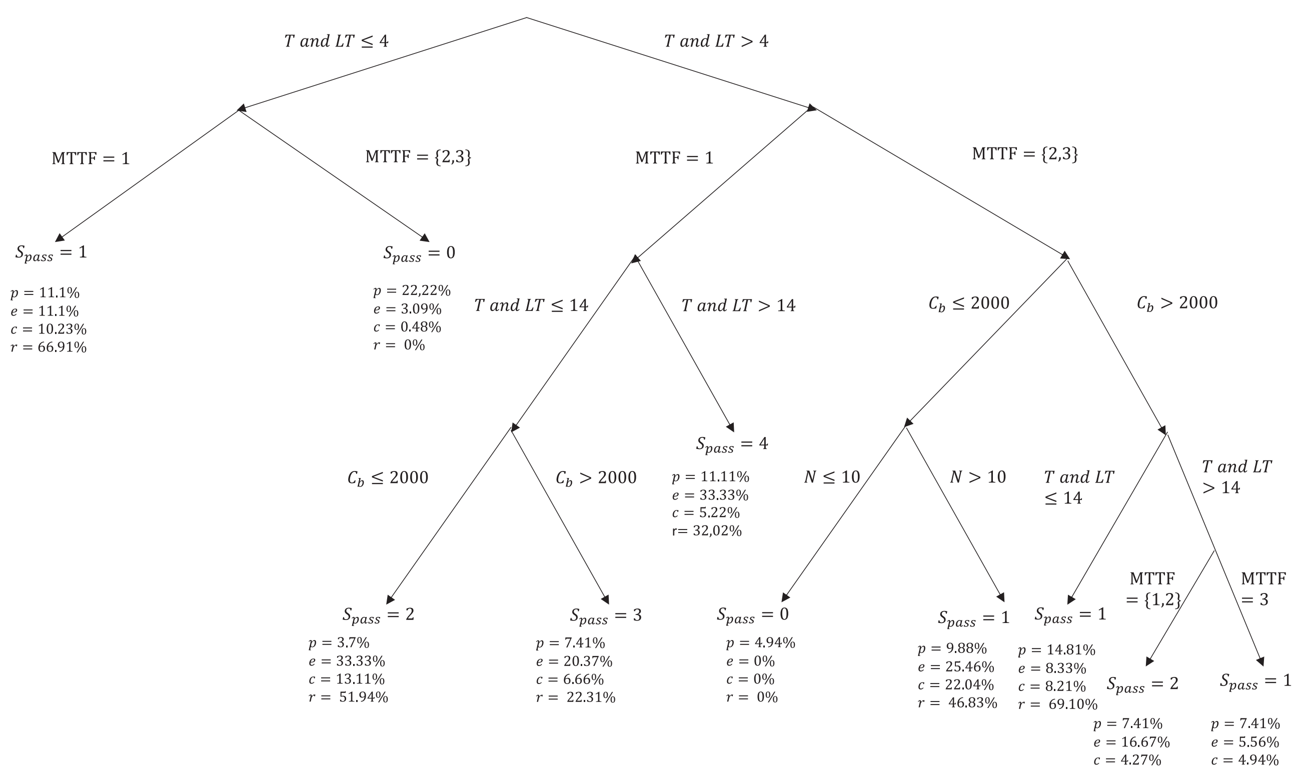

Figure 8. Classification tree on S_{pass}.S_{pass} = 0 means that CM is to be adopted;S_{pass} > 0 means that AM is to be adopted.

Notably, when T and LT are high, the resulting sub-tree suggests a higher S_{pass}, reaching levels of 3 or 4. This illustrates that with longer review periods and lead times, investing in a printer becomes advantageous, even under moderately constrained stock levels. In contrast, for parts with low lead times and review period the classical CM spare parts management become ineffective only with very tight stock constraints. Additionally, the reliability of parts emerges as the other fundamental variable in the splits. Higher reliability ($MTTFlevel = 1$) leads to a higher S_{pass}. This, as expected, reflects the importance of AM for critical spare parts where CM parts' reliability is moderate and lower constraints on the stocks are required to favour AM.

Regarding error percentages and associated costs, higher error percentages are typically associated with scenarios involving fewer instances. The maximum percentage misclassification observed is 33%, occurring in a leaf with only 3.7% of instances. In addition, the misclassification in this leaf results in an average misclassification cost of 13.11% while the average percentage savings in the same leaf for correctly classified instances is 51.94%, demonstrating the benefits of the tree even in the leaf with the highest misclassification. For instance, the leaf with the highest misclassification cost of 22.04% provides an average saving of 46.83% in correctly classified instances. In conclusion, the weighted percentage misclassification cost of the tree is 6.91%, compared to the average weighted saving of 39.10% for correct classification. Thus, out of the previously found average saving of 46.01%, only 6.91% is lost due to tree misclassification even if the original tree has been pruned by a half of its levels. Therefore, the proposed decision tree proves to be a promising tool for assessing the feasibility of AM insourcing, offering simplicity and ease of use with minimal losses due to misclassification.

5. Conclusion

In this study, we developed a cost-based mathematical model able to assess the economic feasibility of managing spare parts across a fleet of systems using either conventional manufacturing (CM) or an on-demand additive manufacturing (AM) approach with insourced printers. The model was tested across 2,187 instances using a full factorial comparison, where we initially found that insourcing a printer was not cost-effective due to high production and printer acquisition costs associated with AM. Subsequently, we re-tested all the instances by constraining the maximum order- up-to level until AM became economically advantageous. The constraints on the maximum order-up-to level fit well current AM industrial application such as remote locations (e.g. offshore platforms), where AM represents a promising application field (Westerweel et al. 2021). This result illustrates the potential for cost savings in stock-constrained systems, with an average cost reduction of 46.01% over the 61.8% of instances where AM became advantageous compared to stocks constrained CM management. This is an important result that justifies the 3D printer insourcing under constrained stock systems. Notably, in 94.47% of cases where AM was feasible, reducing the maximum order-up-to level by only 2 or 3 parts was sufficient. This illustrates how insourcing a printer can be profitable even with modest stock capacity constraints. Additionally, by reducing the printer purchasing cost, the main barrier identified to the adoption of AM, by 5-10-15%, we observed a 10.68% reduction in stock constraints and a 5.09% overall cost reduction for AM compared to the base case. This underscores the importance of cost reductions in AM technology to facilitate broader adoption and improve cost-efficiency.

To further assist managers in decision-making, we developed a decision tree to serve as a DSS for evaluating the economic viability of AM based on parts characteristics and stock capacity constraints. The tree, despite its few levels, achieved effective classification with a low weighted average misclassification cost of 6.91%, compared to an average weighted savings of 39.10% for correct classifications. The decision tree highlights key factors such as lead time and review period, demonstrating that longer review periods and lead times favour AM, even under lighter stock constraints. Conversely, when lead times and review periods are shorter, CM is generally more advantageous unless stock constraints are particularly severe. Another crucial finding is the role of part reliability: lower reliability leads to a higher S_{pass}, highlighting the importance of AM for critical spare parts, since with higher failure rates, backorder costs in CM are high even with light constraint on the order-up-to level.

In summary, this study offers several actionable insights for managers considering AM for spare parts management:

- Unconstrained stock systems: the insourcing of a printer is not convenient with current purchasing costs and only becomes feasible with unrealistic reductions in printer purchasing costs for the near future.
- Stock constrained systems: AM can lead to significant cost savings, even with modest reductions in stock levels. In 68.5% of cases stocks constraints favour AM with an average cost reduction of 46.01%. Additionally, in 90.1% of instances, reducing stock levels by just

2 or 3 parts makes AM economically viable highlighting its efficiency with modest stock constraint.

- Lead time and review period sensitivity: managers should prioritise AM adoption in scenarios where long lead times and review periods exist, as these conditions make the investment in AM more advantageous.
- Critical spare parts: for parts with lower reliability and higher failure rates, AM becomes indispensable due to the high backorder costs in CM.
- Cost barriers: reducing AM-related capital expenses, particularly the purchasing cost of 3D printers, can significantly lighten stock constraints and improve overall cost efficiency, making AM a more feasible option for many organisations.

Looking ahead, the recent industrial focus on printing hubs (Start Us Insight 2024; Verboeket et al. 2021) could be a main driver. This work could hence be extended to such settings, extending actual works such as (Khajavi, Holmström, and Partanen 2018), assessing the feasibility of a print-to-stock approach as a promising Spare Parts Supply Chain (SPSC) configuration using AM. This research direction can include the facility location problem of the hub as well as its design in terms of capabilities and capacity. Furthermore, in light of AM's recent role in addressing the COVID-19 pandemic, future studies could investigate the viability of insourcing printers during disruptions, considering key performance indicators beyond cost.

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Data availability statement

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

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