Impact of Failure Rate Uncertainties on the Implementation of Additive Manufacturing in Spare Parts Supply Chains

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Abstract. The world of spare parts may be revolutionized by the advent of additive manufacturing (AM). Thanks to the possibility to manufacture spare parts on-demand, AM has attracted great attention in the last years as a substitute of conventional manufacturing techniques (CM). However, both researchers and practitioners point out two main limitations that might hinder the transition from CM to AM for the manufacturing of spare parts: AM parts' high production costs and uncertain failure rate. While the former limitation will most likely be overcome in the near future, the latter remains an open issue, so far uninvestigated. We therefore aim to investigate the effect of uncertain failure rate estimates on the optimal inventory level and on the total costs of spare parts management. To do so, we adapt a periodic inventory management policy available in the literature to include failure rate uncertainties and perform a parametrical analysis to investigate their impact varying the mean values of the failure rate, the lead times, and the unitary backorder and production costs. From the results it emerged that the effects of the failure rate uncertainties on the optimal inventory level and on the total costs of spare parts management increases exponentially, leading to a divergence up to 250% for both.

Keywords: Failure rate uncertainty · Spare parts · Additive manufacturing

1 Introduction

Spare parts management represents a crucial aspect in nowadays society where highly available production systems are required. However, efficient spare parts management is often challenging, due to, e.g., intermittent demands (difficult to forecast both in terms of quantity and frequency), strong dependency on suppliers, long procurement lead times, and high downtime costs [1, 2].

Recently, Additive Manufacturing (AM) has emerged as a way to overcome these challenges: AM enables the manufacturing of parts in an economic and fast fashion, in addition to the possibility to manufacture spare parts close to the point of use [3]. By manufacturing spare parts on-demand, AM can reduce the high inventory levels

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necessary to cope with intermittent demand and to avoid the risk of incurring high downtime costs, while, especially when in-sourced, it can decrease the dependency on suppliers. Moreover, AM can positively affect also the environmental footprint by reducing the resource consumption (the amount of raw material required in the supply chain is reduced, as well as the need wasteful and polluting manufacturing processes) and the emissions of air pollutant from transportation (spare parts can be manufactured close to the point of use) [4].

Consequently, driven by the potential benefits of lower inventory levels, overall costs and environmental footprint, researchers and practitioners have started investigating the suitability of AM in the spare parts management field, evaluating under which conditions (e.g., demand, backorder costs, lead times, etc.) AM was economically beneficial, including also considerations about the possibility to produce spare parts directly on the point of use [5–8]. However, these results highly rely on the assumptions and on the parameters considered, especially on the consideration of different mechanical properties between AM and conventional manufacturing (CM) parts. Westerweel et al., for example, adopting a lifecycle cost analysis where different designing costs and potential benefits associated with AM parts were also considered, confirmed the high impact of mechanical properties differences on the profitability of AM as manufacturing technique [7]. Mechanical properties like tensile and fatigue strength, in fact, determine when the failure of a part will occur (and hence its failure rate): under the same working conditions, the higher the mechanical properties, the later in time the part will fail. Whereas in the pioneering works the mechanical properties of AM and CM parts were considered identical, it has recently become common practice to consider AM parts characterized by lower mechanical properties (and hence by higher failure rates) than CM counterparts [9]. However, although the assumption of lower mechanical properties held true in the past when AM techniques started being investigated, the use of post-process operations (e.g., polishing, Hot Isostatic Pressing, and Annealing) has recently shown to lead to mechanical properties equal or even higher than those of CM parts [10–12]. This was confirmed by Sgarbossa et al., who, investigating the scenarios for which the use of AM for spare parts management would result economically beneficial over CM, deployed an interdisciplinary approach in which they derived AM mechanical properties with material science techniques for different AM techniques and post-processing combinations [13].

From the analysis of these works, it emerges that a current characteristic feature of AM parts is the mechanical properties uncertainties, which might hinder their use. Westerweel et al., for example, stated that *"a current limitation of AM technology is that there is often uncertainty concerning the mechanical properties of such parts"* [7]. Similarly, Knofius et al. reported that together with high unit cost *"low and uncertain reliabilities of printed parts often rule out the use of AM"* [9]. The uncertainty in the mechanical properties corresponds in turn to the uncertainty in the failure rates, which represents, however, an overlooked issue.

The effects of failure rate uncertainties have only recently started being investigated for CM parts. Specifically, van Wingerden et al. evaluated their impact on the holding costs and on the number of backorders [14]. However, dealing with AM, despite failure rate uncertainties even higher than those of the CM parts (due to the limited knowledge of these techniques) and their assumed importance, no one has addressed this problem yet to the best of our knowledge. It thus remains unclear to which extent failure rate uncertainties impact the benefits of AM in spare parts supply chains. This work represents a first step and will investigate the effects of failure rate uncertainties on the total cost and the optimal inventory policy. To model the failure rate uncertainty, we considered the failure rate not to be known precisely but to be normally distributed with a certain mean value (λ) and with a standard deviation σ. The effects of these uncertainties on the optimal inventory level and the total costs of spare parts management were then determined through a parametrical analysis considering more 7,500 scenarios derived from practice, and the results are reported in Sect. 3. Details about the methodology used can instead be found in Sect. 2.

It is worth mentioning that the main goal of this work is that of rendering clear to the scientific community the great errors that would be committed by neglecting the failure rate uncertainties.

2 Method

To understand how the failure rate uncertainties can impact the optimal inventory level and the total costs of spare parts management, we carried out a parametrical analysis where 7,500 different scenarios were developed. Specifically, first we developed the benchmark solution where we assumed the failure rate to be known. Here, the optimal inventory level and the total costs of spare parts management were determined considering the periodic review model with Poisson distributed demand also used by Sgarbossa et al. [13]. It is worth mentioning that this model holds true only when we are in the "random failures" area of the bathtub curve [15]. The total costs C_{tot} has been measured according to Eq. 1, and it is defined as the sum of holding costs C_h, backorder costs C_b and production costs C_p, which are in turn defined in Eqs. 2, 3 and 4, respectively.

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

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

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

$$C_p = \lambda \cdot c_p, \tag{4}$$

where S is the order-up-to-level, y is the stochastic demand (i.e., the number of failures in the period $T + L$), L is the lead time, T is the review period, h is the holding cost rate, c_p and c_b are the unitary production and backorder costs, respectively, λ is the failure rate and $P_{\lambda,T+L,y}$ is the probability of having y failures over the period $T + L$ given the failure rate λ.

The optimal inventory level S^* is the order-up-to-level that minimizes the total costs.

Second, we adapted the formulas to take into consideration the failure rate uncertainties. Specifically, we considered the uncertainty in the failure rate to follow a normal distribution, leading to the holding costs C_h, backorder costs C_b and production costs C_p to be now modelled according to Eqs. 5, 6 and 7, respectively.

$$C_h = h \cdot c_p \cdot \int_0^{\infty} f(x) \cdot \sum\nolimits_{y=0}^{S-1} (S-y) \cdot P_{x,T+L,y} dx; \tag{5}$$

$$C_b = c_b \cdot \int_0^{\infty} f(x) \cdot \sum\nolimits_{y=S+1}^{\infty} (y-S) \cdot P_{x,T+L,y} dx; \tag{6}$$

$$C_p = c_p \cdot \int_0^{\infty} f(x) \cdot x dx, \tag{7}$$

where x is a random variable following a normal distribution N with mean λ and standard deviation σ. The associated probability density function is expressed by $f(x)$.

Then, we carried out the parametrical analysis considering 7,500 different scenarios using data obtained from discussions with experts in the field and from the literature [8, 9, 13]. Specifically, we aimed to cover different spare parts supply chain scenarios. We considered three values of the unitary backorder cost c_b in order to cover three possible situations (i.e., low, medium and high costs related to production losses), nine values of the cost ratio $\frac{c_b}{c_p}$ (from now on we will refer to this simply as *cost ratio*) to cover different part sizes and materials (big and metallic parts are covered considering low cost ratios, while small and plastic parts are considered with high cost ratios), five values of failure rate λ to consider different part consumptions, five values of the lead time L to include both in-source and out-source AM production (0.2 week, which corresponds to one working day, and 0.6 week, which corresponds to three working days reflect the in-source production, while 1, 1.5 and 2 weeks reflect the out-source production), and ten values of uncertainties in the failure rate, expressed through the standard deviation σ. Specifically, the values of the failure rate were chosen considering the suggestions of Knofius et al. [9]. They reported, in fact, that AM is perceived valuable in low-volume applications, i.e., "*on scenarios where the combination of failure rate and installed base size causes 1 to 7 demands per year*". Based on this, we considered in our work scenarios where the spare parts demand ranges from 4 parts per year to 1 part every 3 years. The different values considered for the analysis are reported in Table 1.

Table 1. Parameters adopted in the parametrical analysis.

Parameters	Value(s)	Unit
Unitary backorder cost (c_b)	5,000; 25,000; 50,000;	€/week
λ	0.005; 0.01; 0.02; 0.04; 0.08	1/weeks
L	0.2; 0.6; 1; 1.5; 2	Weeks
Cost ratio $\left(\frac{c_b}{c_p}\right)$	20; 40; 60; 80; 100; 120; 140; 160; 180; 200	-
Standard deviation (σ)	5; 10; 15; 20; 25; 30; 35; 40; 45; 50	%

Another input parameter is the holding rate h which was assumed constant and equal to 0.58% of the production cost on a weekly basis (it is common practice to consider it equal 30% of the production cost on a yearly basis [16]). It is worth mentioning that the standard deviation is given as percentage of the mean value (i.e., λ), and we consider that the order for AM can be placed every L periods, meaning that $T = L$.

Finally, we considered the effects of failure rate uncertainties on the optimal inventory level and on the total costs as difference with the benchmark solution. Specifically, the effects of failure rate uncertainties on the optimal inventory level were considered through the parameter ΔS^* (Eq. 8), while those on the total costs through the parameter ΔC_{tot} (Eq. 9).

$$\Delta S^* = S^*_{uncertainty} - S^*_{benchmark}; \tag{8}$$

$$\Delta C_{tot} = \frac{C_{tot,uncertainty} - C_{tot,benchmark}}{C_{tot,benchmark}} \cdot 100, \tag{9}$$

$S^*_{uncertainty}$ and $S^*_{benchmark}$ represent the optimal inventory level and $C_{tot,uncertainty}$ and $C_{tot,benchmark}$ the total costs with uncertain failure rate and known failure rate, respectively. The parameter ΔC_{tot} is expressed in percentages.

3 Results and Discussions

The results of the parametrical analysis were then used as inputs in a main effects analysis to understand the importance of the various parameters on ΔS^* and ΔC_{tot}, and the results are reported in Fig. 1 and Fig. 2, respectively.

From the main effects plot it is interesting to see that the unitary backorder cost c_b affects neither ΔS^* nor ΔC_{tot}, but what matters (in terms of costs) is the ratio $\frac{c_b}{c_p}$. This can be explained mathematically. Starting from the latter, considering Eq. 9, if we introduce in the formula the ratio $\frac{c_b}{c_p}$ (by simply dividing Eq. 9 by c_p) and if we render it explicit, we obtain the following:

$$\begin{aligned}\Delta C_{tot} &= \frac{\left(h\cdot\int_0^\infty f(x)\cdot\sum_{y=0}^{S-1}(S-y)\cdot P_{x,T+L,y}dx + \frac{c_b}{c_p}\cdot\int_0^\infty f(x)\cdot\sum_{y=S+1}^{\infty}(y-S)\cdot P_{x,T+L,y}dx + c_p\cdot\int_0^\infty f(x)\cdot x dx\right)}{\left(h\cdot\sum_{y=0}^{S-1}(S-y)\cdot P_{\lambda,T+L,y} + \frac{c_b}{c_p}\cdot\sum_{y=S+1}^{\infty}(y-S)\cdot P_{\lambda,T+L,y} + \lambda\right)} \\ &- \frac{\left(h\cdot\sum_{y=0}^{S-1}(S-y)\cdot P_{\lambda,T+L,y} + \frac{c_b}{c_p}\cdot\sum_{y=S+1}^{\infty}(y-S)\cdot P_{\lambda,T+L,y} + \lambda\right)}{\left(h\cdot\sum_{y=0}^{S-1}(S-y)\cdot P_{\lambda,T+L,y} + \frac{c_b}{c_p}\cdot\sum_{y=S+1}^{\infty}(y-S)\cdot P_{\lambda,T+L,y} + \lambda\right)}\end{aligned} \tag{10}$$

It can be seen that ΔC_{tot} does not depend on the unitary backorder cost c_b, hence explaining the results reported in the main effects plot. Moreover, since the optimal inventory level S^* is the order-up-to-level that minimizes the total costs, if these do not depend on the unitary backorder cost c_b, then neither the ΔS^*. It is worth mentioning

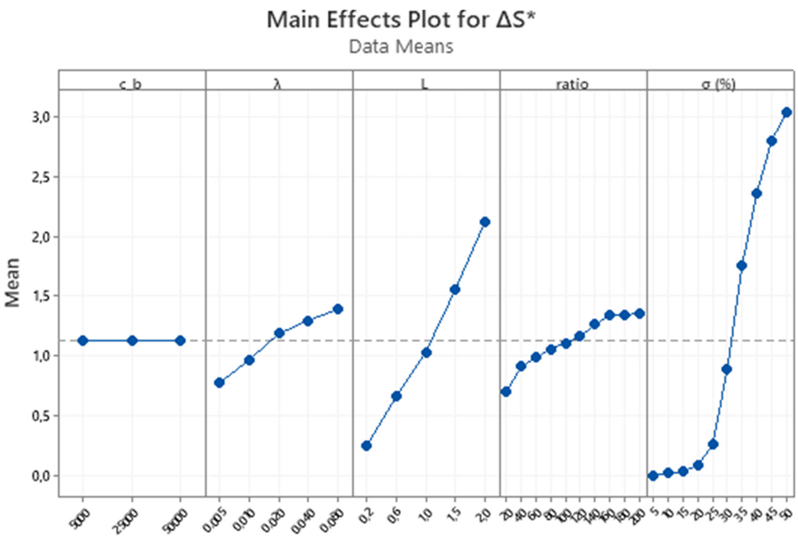

Fig. 1. Main effects plot for ΔS^{*}, where c_b is the unitary backorder cost, λ the failure rate, L the lead time, $\frac{c_b}{c_p}$ the cost ratio (i.e., the ratio between the unitary backorder costs and the unitary production costs), and σ the standard deviation.

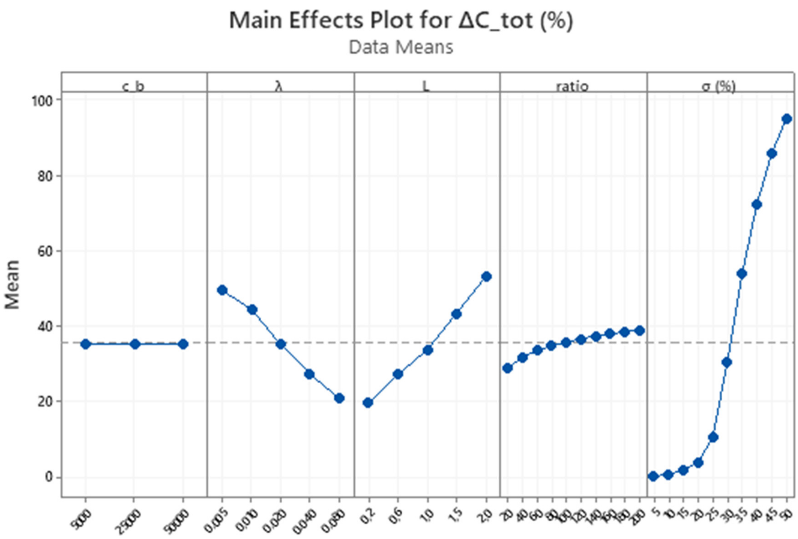

Fig. 2. Main effects plot for ΔC_{tot}, where c_b is the unitary backorder cost, λ the failure rate, L the lead time, $\frac{c_b}{c_p}$ the cost ratio (i.e., the ratio between the unitary backorder costs and the unitary production costs), and σ the standard deviation.

that this holds true only in this case since we consider the differences and the relative differences for the optimal inventory levels and for the total costs, respectively: if we had considered the absolute values this would have not held true.

The main observation, however, is the fact that the failure rate uncertainties (σ) affect both ΔS^* and ΔC_{tot}, and that their effect increases exponentially. Specifically, the effect remains contained on both ΔS^* and ΔC_{tot} for $\sigma < 20\%$, for then diverging. Indeed, with $\sigma > 20\%$, 97% of the times the optimal inventory level is higher than that of the benchmark solution, while the percentage variation in the total costs ΔC_{tot} varies from 4% to 242% (ΔC_{tot} is always lower than 7% when $\sigma < 20\%$). Specifically, the lower variations occur when the lead times are low and the failure rates are high, while the higher variations when the lead times are high and the failure rates are low.

From this, it emerges the need to keep the failure rate uncertainties as low as possible in order to minimize the mistakes that would be made otherwise by neglecting it in the spare parts management. To do so, it is fundamental that researchers and practitioners in the material science field focus on two different and concurrent aspects, i.e. (i) a mechanistic knowledge of the failure behavior of AM parts and (ii) an improved monitoring of the AM manufacturing processes. The former, achievable through an experimental and theoretical understanding of the behavior of AM components, would in fact allow practitioners and researchers to be able to accurately determine the microstructure of a specific part just by knowing the process parameters used and then to relate it to a precise estimation of the mechanical properties (and hence of the failure rate) thanks to a plethora of experimental data (data-driven approach) [12]. The second aspect, then, would favor a more precise determination of the failure rate by carrying out in-situ observations during the manufacturing of the parts: by knowing the shape and heat distribution of the melt pool it is in fact possible to predict the presence of defects within the parts, and hence to estimate the mechanical properties (and hence of the failure rate) thanks to the knowledge developed in aspect (i) [17].

4 Conclusions and Future Research

In this work we aim to understand the impact of failure rate uncertainties on the optimal inventory level and on the total costs of spare parts management. This represents in fact a very important issue that has however been overlooked by researchers and practitioners despite its well-known importance. Researchers and practitioners, in fact, have focused on understanding under which conditions (failure rates, production and backorder costs, lead times, locations of the facilities, etc.) the transition from CM to AM for producing spare parts is beneficial, but they have completely overlooked the failure rate uncertainties despite their well-known importance for the final suitability of AM. In this work we have hence addressed this topic, with the principal purpose of render clear to the scientific community the great errors that would be committed by neglecting the failure rate uncertainties.

To do so, we modify a periodic review model to consider failure rate uncertainties and we carried out a parametrical analysis considering 7,500 different scenarios. From the results it emerged that the failure rate uncertainties (σ) has an exponentially increasing effect both on the optimal inventory level and on the total costs (evaluated through ΔS^* and ΔC_{tot}, respectively). This confirms the assumption reported in the literature that mechanical properties uncertainties (and hence failure rate uncertainties) are a major hold back on the switch from CM to AM for the manufacturing of spare parts. Only minor failure rate uncertainties are thus acceptable to build efficient spare parts supply chains with AM, and from our analyses a limit of 20% seems to be sufficient. In fact, from our finding, almost 97% of the times that $\Delta S^* > 0$ σ was greater than 20%. Similarly, the impact on the total costs is limited when $\sigma \leq 20\%$ (the percentage variation in the total costs ΔT_c is always lower than 7%). However, further analyses are needed to confirm the validity of 20% as limit.

Based on these results, it should emerge clearly the importance of including the failure rate uncertainties in the spare parts management analysis, and practitioners can use the modified periodic model reported in Eqs. 5–7 to determine the order-up-to-level that considers their values of the failure rate uncertainties. Moreover, based on these results, we aim to point out the need for researchers and practitioners in material science to reduce the uncertainty in the failure rate, and this can be achieved through a combined approach that aims to increase both the knowledge of the failure behavior of AM parts and the monitoring operations of the AM manufacturing processes. This represents a fundamental step for exploiting the full benefits of AM for spare parts management since it will break down one of the two main barriers limiting its use.

Moreover, managers need to be assisted in the decision of the best sourcing option (CM or AM). Although we discussed in Sect. 1 that something has already started moving, much still needs to be done. This will represent the main focus of our future research activities, where we will focus on the development of a robust DSS able to handle the failure rate uncertainties to ensure the correct decision about sourcing options, so whether a spare part should be produced using AM or CM, and this work represents a crucial milestone of our future research activities, without which we could not go ahead. It is in fact fundamental to understand the correct impact of the failure rate uncertainties to be able to develop such a robust DSS.

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