

Optimizing Spare Parts Inventory Management: the Joint Replenishment Problem with Additive Manufacturing

Lolli F. *, Coruzzolo A.M. *, Balugani E. *,

* *Department of Sciences and Methods for Engineering (DISMI), University of Modena and Reggio Emilia, Via Amendola 2 – Padiglione Morselli, 42100 Reggio Emilia, Italy*

Abstract: In today's complex industrial landscape, managing spare parts inventory is essential for ensuring operational continuity and minimizing downtime costs. However, traditional inventory management strategies often struggle to keep up with the sector's dynamic demands. In this research, for the first time, we applied the well-known Joint Replenishment Problem (JRP) alongside Additive Manufacturing (AM) to optimize spare parts inventory management. Specifically, we benchmarked the joint replenishment of Classical Manufacturing (CM) parts with AM ones, both investigated under a periodic review policy. Notably, we found that while individual spare parts are more cost-effective with AM, joint management is most efficient with CM unless a 30% reduction in printing costs is achieved.

Copyright © 2025 The Authors. This is an open access article under the CC BY-NC-ND license (<https://creativecommons.org/licenses/by-nc-nd/4.0/>)

Keywords: Spare Parts, Inventory management, Additive Manufacturing, Joint Replenishment Problem

1. INTRODUCTION

In today's manufacturing environments, where high levels of automation have been achieved through significant investments, ensuring high machine availability is essential (Dellagi et al., 2020) to prevent system downtime, which can result in substantial financial losses. Consequently, spare parts must be readily available to repair machinery when required. However, traditional spare parts management, relying on Classical Manufacturing (CM) from Original Equipment Manufacturers (OEMs), often results in high stock levels, increasing costs and exposing companies to the risk of obsolescence. This risk is particularly significant in industries with short product life cycles or rapidly evolving technologies (Pinçe et al., 2021). High stock levels in CM spare parts management are maintained to address the intermittent and difficult-to-forecast nature of spare parts demand (Babai et al., 2021; Boylan & Syntetos, 2010), as well as the long lead times associated with OEMs. Additive Manufacturing (AM) offers a promising alternative for managing spare parts, particularly due to its capacity for on-demand production (Y. Li et al., 2017). This flexibility allows companies to reduce or even eliminate safety stock, as AM enables the production of a wide variety of parts with a single system, thereby minimizing downtime and inventory costs. Furthermore, AM technologies have significantly evolved in recent years, enabling the production of complex geometries with minimal setup time (Gibson et al., 2015; Wong & Hernandez, 2012). For example, AM is increasingly applied in industries such as healthcare and aerospace, where parts must meet stringent precision and durability standards (S. Liu & Shin, 2019; Regis et al., 2015). However, the high costs of AM equipment and limited understanding of the reliability of AM parts under various operational conditions remain significant barriers to widespread adoption in spare parts management (Knofius et al., 2019). While current practical applications are mostly limited to remote locations and emergency situations (Magazine Additive Manufacturing, 2023; Westerweel et al., 2021), the literature has proposed various quantitative models to assess the economic feasibility of managing spare parts

using AM. These quantitative models were preceded by qualitative and empirical investigations. Among the earliest contributions, Holmström et al., (2010) emphasized the need for quantitative research in this field. Khajavi et al., (2014) analysed the costs of centralized and decentralized AM for the F-18 Super Hornet's spare parts supply chain, shedding light on AM-related costs but lacking a direct comparison with CM. Liu et al., (2014) addressed this gap by comparing AM and CM in aircraft spare parts supply chains, demonstrating that AM could reduce inventory levels by up to 70% compared to CM. Li et al., (2016) extended this analysis by including production and purchasing costs, confirming that while AM is advantageous when considering only inventory costs, CM remains preferable when full cost structures are accounted for. Westerweel et al., (2018) further refined this approach by developing a lifecycle-based mathematical model to determine the break-even point between AM and CM, highlighting the importance of fixed and variable costs. Zhang et al., (2019) evaluated AM's potential for on-demand supply, concluding that while AM offers flexibility, it struggles with cost competitiveness and efficiency compared to traditional warehousing due to batching and part-size limitations. (Heinen & Hoberg, 2019) adopted a holistic approach combining case studies and modeling, while Knofius et al., (2019, 2021) emphasized dual sourcing strategies, where CM is used for regular supply and AM for emergencies, achieving cost savings exceeding 30% compared to single-sourcing strategies. Song & Zhang, (2020) proposed a mathematical model to manage multi-part queues at AM printers, while Sgarbossa et al., (2021) investigated the profitability of AM with a multidisciplinary approach that considered post-processing and production techniques. Building on this research, (Peron et al., 2024) evaluated the impact of uncertainties in AM failure rates, proposing strategies to mitigate their economic implications. Similarly, (Lolli et al., 2024) delved into the on-demand production of spare parts for constrained stock systems, offering practical guidelines for printer insourcing. More recently, Roozkhosh et al., (2024) integrated mathematical modelling, simulation, and machine learning to examine adaptive, decentralized, and centralized

multi-level supply chains using AM, demonstrating reductions in cost and uncertainty. Lastly, Mecheter et al., 2024) utilized a multi-period mixed-integer linear programming model to evaluate AM’s profitability in multi-period, multi-part environments. They concluded that AM is most cost-effective for complex geometries, while CM remains better suited for larger, simpler parts. However, their research did not consider the joint replenishment of parts and only analysed nine different components. As demonstrated and confirmed by recent literature reviews (Coruzzolo et al., 2022; Kulshrestha et al., 2024; Mecheter et al., 2023), the Joint Replenishment Problem (JRP) has yet to be explored in the context of AM spare parts management. This contrasts with findings in broader JRP literature, which show that ignoring the correlated consumption of spare parts leads to inefficiencies (Li & Schmidt, 2020). To address this gap, our work applies the Stochastic Joint Replenishment Problem (SJR) framework, which optimizes lot sizes and delivery schedules for spare parts while minimizing total costs, including ordering, holding, and backordering (Fung et al., 2001; Goyal & Satir, 1989; Rempala, 2003). Specifically, we implemented a periodic review (T, S) policy for JRP, as proposed by Moharana & Sarmah, (2018) evaluating CM and AM spare parts management. Additionally, we assessed potential clustering using hierarchical clustering methods supported by the Jaccard index, calculated in three different ways. Our contribution lies in applying the JRP to AM parts for the first time, comparing their management costs to CM parts while clustering spare parts using hierarchical clustering algorithms. The paper is structured as follows: Section 2 details the methods followed while Section 3 presents our preliminary results. Lastly, Section 4 contains our conclusions and outlines avenues for future research.

2. METHODS

This section presents the reordering policy applied (Section 2.2) and the hierarchical clustering techniques (Section 2.3). These are preceded by the notation used (Section 2.1) and concluded with the method followed to construct the dataset under analysis (Section 2.4).

2.1 Notation

Here, we present the notation used throughout this work. For the reordering policy, we generally refer to clusters of spare parts, which may consist of either CM or AM parts.

- m = number of spare parts, produced via CM or AM.
- f = number of orders involving the spare parts considered.
- TR = matrix containing the set of orders involving the spare parts considered. $TR(e, f) = 1$ if in order- e the spare parts- f was included 0 otherwise.
- SUB_X = sub-transaction matrix involving the orders of parts in cluster- X available in TR .
- n = number of spare parts in the specific cluster considered.
- i = index of i^{th} part of the cluster, with $i = 1, \dots, n$.
- $I = \{I_1, I_2, \dots, I_m\}$ set of spare parts.

- Dendrogram $DE =$ ordered set of tuples $\langle R, Sim, q, L^{(R)}, C^{(R)} \rangle$, where R is the hierarchy level, Sim is the similarity measure exploited to assess clusters similarity, q is the number of clusters at the R^{th} hierarchy level, $L^{(R)}$ is the set of clusters generated at the same level while $C^{(R)}$ is the total cost for the joint management of the R^{th} level of the hierarchy. Note that if $R = 1$ it implies that $q = m$ thus parts are managed individually and $C^{(1)}$ equals the total cost for the individual management of the parts.
- R^* = optimal hierarchy level i.e., hierarchy level that guarantees the minimum $C^{(R)}$.
- $G^{(R+1)}$: candidate cluster set that contains all possible clusters to generate $L^{(R+1)}$.
- l_{iAM} = demand rate of the i^{th} AM part of the cluster, with $i = 1, \dots, n, [\frac{part}{week}]$.
- l_{iCM} = demand rate of the i^{th} CM part of the cluster, with $i = 1, \dots, n, [\frac{part}{week}]$.
- a_i = minor order cost for the i^{th} part of the cluster, with $i = 1, \dots, n, [\frac{\epsilon}{order}]$.
- h_i = stocking cost for the i^{th} part of the cluster, with $i = 1, \dots, n, [\frac{\epsilon}{week \cdot part}]$.
- π_i = shortage cost for the i^{th} part of the cluster in shortage, with $i = 1, \dots, n, [\frac{\epsilon}{part}]$.
- L_i = lead time for the i^{th} part of the cluster [week].
- L_{CM} = common lead time for parts produced via CM [week].
- L_{AM} = common lead time for parts produced via AM [week].
- S_i = order up to level of i^{th} part of the cluster, with $i = 1, \dots, n$.
- T_i = reorder period of i^{th} part of the cluster, with $i = 1, \dots, n$.
- T_0 = base order up to level of the cluster.
- x_i = variable following a poisson distribution to represent the failure of the i^{th} part of the cluster, with $i = 1, \dots, n$.
- $C_{tot_{ind}}$ = total cost for the independent management of a spare part $[\frac{\epsilon}{week}]$.
- $p(x_i)$ = probability density function of x_i , with $i = 1, \dots, n$. $p(x) = \frac{[\lambda_i(T_i+L_i)]^{x_i} x_i e^{-[\lambda_i(T_i+L_i)]}}{x_i!}$.
- $C_{tot_{ind}}$ = total cost for the independent management of a spare part $[\frac{\epsilon}{week}]$.
- $C_{tot_{jo}}$ = total cost for the joint management of a cluster of spare parts $[\frac{\epsilon}{week}]$.

2.2 JRP reordering policy

Here we detail the reordering policy applied. In particular, among the different available policies developed for the JRP we have chosen to apply the periodic review policy of Moharana and Sarmah (2018) since period review is more appropriate for the intermittent demand that characterizes

spare parts (Boylan & Syntetos, 2010). In (1) we reported the cost for the individual management of a part as proposed in Moharana and Sarmah (2018) while (2) shows the cost for the joint management of a cluster.

$$C_{tot_{ind}} = \frac{A+ai}{T_i} + hi\left(\frac{\lambda_i * T_i}{2} + \sum_{x_i=0}^{S_i} (S_i - x_i) * p(x_i)\right) + \frac{\pi_i}{T_i} (\lambda_i (T_i + L_i) - Si + \sum_{x_i=0}^{S_i} (S_i - x_i) * p(x_i)) \quad (1)$$

$$C_{tot_{jo}} = \frac{A+\sum_{i=1}^n \frac{a_i}{k_i}}{T_0} + \sum_{i=1}^n h_i \left(\frac{\lambda_i * T_i}{2} + \sum_{x_i=0}^{S_i} (S_i - x_i) * p(x_i) \right) + \sum_{i=1}^n \frac{\pi_i}{T_i} (\lambda_i (T_i + L_i) - S_i + \sum_{x_i=0}^{S_i} (S_i - x_i) * p(x_i)) \quad (2)$$

Having obtained for each level of the hierarchy- R the cost for the item managed individually with (1) and the cost for the parts managed jointly with (2) their sum equals to $C^{(R)}$. Then the hierarchy level that guarantees the minimum $C^{(R)}$ is the optimal one, denoted as R^* . To optimize (1) and (2) we followed the approach outlined by Moharana and Sarmah (2018), to which the reader is referred for further details. This approach has been applied to both AM and CM parts separately as previously indicated. Then the R^* for each production technology have been compared.

2.3 Hierarchical Clustering

To carry out the hierarchical clustering of AM or CM parts we exploit the classical hierarchical clustering as proposed in Tsai, Tsai and Huang (2009) and Moharana and Sarmah (2018) with different similarity measures. Indeed, we exploit the Jaccard Index. Given a transaction matrix Tr , that is a 0-1 matrix where T_{ij} equals to 1 if spare part- i was included in transaction- j and two clusters of spare parts (X_1 and X_2) that pertains to two different sub-transactions matrix SUB_{X_1} and SUB_{X_2} , the Jaccard Index is calculated as shown in (3).

$$J(X_1, X_2) = \frac{|SUB_{X_1} \cap SUB_{X_2}|}{|SUB_{X_1} \cup SUB_{X_2}|} \quad (3)$$

In practice, it represents the intersection in terms of number of shared transactions divided by the size of the union of the transactions that involved the parts. We exploited the Jaccard index calculated as average linkage, representing the average index between two clusters; single linkage, corresponding to the maximum index between two clusters; and complete linkage, indicating the minimum index between two clusters.

2.4 Dataset construction

Given the absence of real, large datasets of spare parts produced via Additive Manufacturing (AM), we decided to generate transactions based on the failure rates of parts. Sgarbossa et al. (2021) employed a multidisciplinary approach to determine the ratio between the failure rates of CM and AM parts. Among the various AM production techniques and post-processing methods, Sgarbossa et al. (2021) identified Selective Laser Melting with Polishing (SLM+P) as the optimal AM technology combination for small parts. For consistency, we considered AM parts produced using SLM+P and compared them with CM parts produced via Casting with subsequent polishing (C+P). This approach allowed us to utilize the failure rate ratio of 6.93 between these two

production methods. The lower and upper limits of the CM parts' failure rate, based on the values used in the full factorial comparison in Sgarbossa et al. (2021), are as follows: $\lambda_{CM}^{inf} = 0.0064$, $\lambda_{CM}^{sup} = 0.096$. While the lower and upper limits of AM spare parts have been obtained dividing the ones of CM part times 6.93: $\lambda_{AM}^{inf} = 9.24 \cdot 10^{-4}$, $\lambda_{AM}^{sup} = 1.38 \cdot 10^{-2}$. To generate the transaction matrix involving parts made either via AM or CM, assuming one transaction or order per day, we followed these steps:

1. Set the number of parts to 100.
2. Set the number of total transactions to 100,000.
3. Obtain the failure rate of each part generating 100 uniformly distributed values in the range $[\lambda^{inf}, \lambda^{sup}]$.
4. Generate for each part for each day a failure based on their λ .
5. Based on the generated failures of the parts populate the transaction matrix.

3. RESULTS

This section presents the results of our preliminary study. First, we discuss the hierarchical clustering of spare parts, followed by the outcomes of their optimized inventory management. Figure 1 illustrates the hierarchical clustering of spare parts produced via CM or AM, based on the generated dataset described in Section 2.4, using the Jaccard index calculated with the single linkage method. Figures 2 and 3 depict the hierarchical clustering results using the Jaccard index calculated with complete and average linkage methods, respectively. The clustering results reveal distinct behaviors based on the chosen linkage method. When using the Jaccard index with single linkage, spare parts with similar failure rates are clustered individually, ultimately forming a single large cluster at the final hierarchy level. In contrast, the complete linkage method tends to create fewer but denser clusters before merging all parts into one cluster at the top of the hierarchy. Lastly, the average linkage method provides a balanced outcome, yielding a moderate number of clusters containing similar spare parts. These observations, as evident from the figures, are consistent across both CM and AM spare parts clusters. After describing the hierarchical clustering of parts produced via AM and CM, we now present the results concerning the costs associated with their management. Notably, the management costs decrease as the hierarchy level increases, irrespective of the production technology or clustering approach. This decrease is attributed to the uniform generation of parts within a relatively narrow interval of failure rates, leading to characteristics that naturally reduce the management costs of parts at higher hierarchy levels. This trend is evident in Figure 4, which illustrates the weekly management costs of parts when clustering is performed using the Jaccard index calculated with the average linkage method. Additionally, the figure incorporates scenarios involving cost reductions for AM parts. Specifically, we simulated a progressive reduction in AM parts printing costs to determine

the threshold at which managing all parts together with AM becomes advantageous over CM.

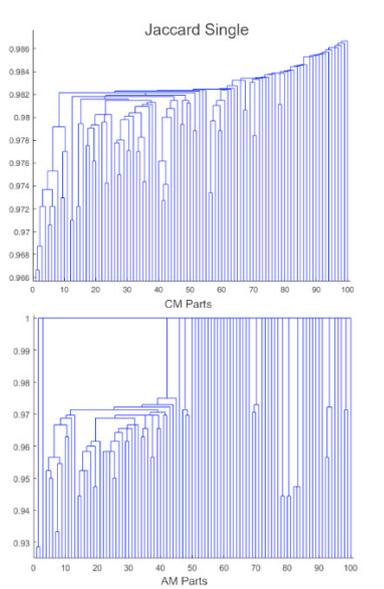


Fig. 1. Hierarchical clustering of spare parts made with CM or AM with Jaccard Single.

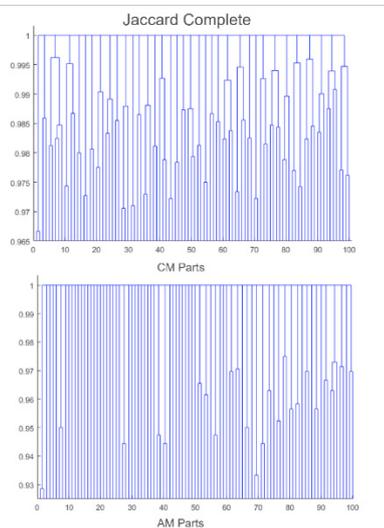


Fig. 2. Hierarchical clustering of spare parts made with CM or AM with Jaccard Complete.

Figure 4 reflects this, showing the management costs for AM parts under varying cost-reduction scenarios: no reduction, 10%, 20%, and 30%. As shown in Figure 4, individual management of parts using AM is more cost-effective than using CM. Specifically, as detailed in Table 1, the cost for managing parts individually with AM is 28.3% lower than with CM. This observation holds true across all the hierarchical clustering because the first and last levels are identical, regardless of the clustering measure employed. This finding is of significant industrial relevance, highlighting the critical role of AM in optimizing spare parts management. In particular, when spare parts are managed using AM, their optimized order-up-to level is consistently one across all hierarchy levels. This means that only one AM part is kept in stock and reordered immediately upon failure of the operating part. This "one-for-one" strategy minimizes both inventory

holding costs and shortages, as the reduced lead time of AM parts effectively shields the system from downtime.

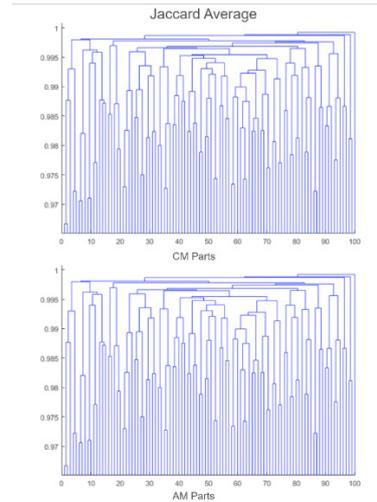


Fig. 3. Hierarchical clustering of spare parts made with CM or AM with Jaccard Average.

In contrast, CM individual management requires an average order-up-to level of 4.6 parts to mitigate system downtime risks, resulting in higher holding costs. Additionally, the mean revision period for parts managed via CM is approximately 130 days, compared to AM, where the revision period is 6.07 times longer. This disparity aligns with the ratio between their failure rates (6.93, as reported by Sgarbossa et al., 2021). The dynamics of cost-effectiveness shift when considering the joint management of all parts. As illustrated in Figure 4, managing all parts together using CM significantly reduces costs, nearly 50%, compared to individual CM management. This substantial reduction makes the joint management of parts via CM not only more cost-effective than their individual management with AM but also less expensive than the joint management of all parts with AM. Specifically, the joint management of all part cost with AM is 35.60% higher than with CM, as detailed in Table 1. Thus, the analysis reveals that CM benefits more from transitioning to joint management, achieving a cost reduction of 51.10% when moving from individual to ensemble management. In contrast, AM only gains a modest 7.5% reduction under the same conditions. This difference arises because AM parts, under individual management, already operate at their lowest feasible order-up-to level. Meanwhile, CM parts reduce their average order-up-to level from 4.6 in individual management to 2.8 in the final hierarchy level, significantly decreasing holding costs. Similarly, the mean revision period for CM parts decreases from 130 days in individual management to 50 days in joint management. This reduction is attributed to the increased risk of part failure in joint management, necessitating shorter revision periods. Furthermore, the absence of revision costs in this model enhances the cost-effectiveness of CM joint management. However, the scenario changes favorably for AM when a 30% reduction in printing costs is achieved. Under such conditions, AM becomes the most cost-effective sourcing option across all hierarchy levels.

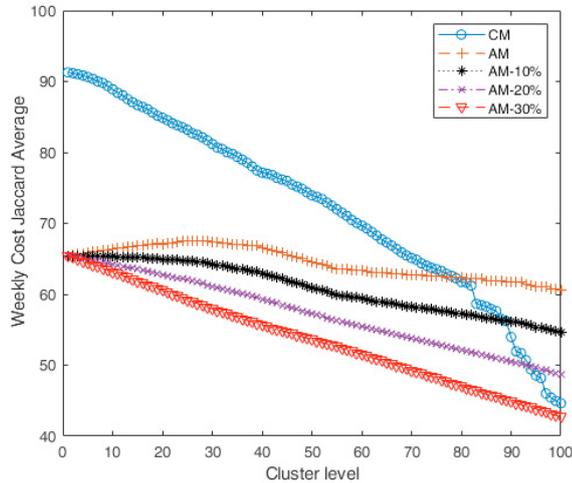


Fig. 4. Weekly cost for the joint management of spare parts made with CM or AM with Jaccard Average.

Table 1. Cost for the individual management of parts vs joint management of all parts

	CM	AM	AM-10%	AM-20%	AM-30%
Weekly cost for individual management of parts [$\frac{\text{€}}{\text{week}}$]	91.20 €	65.40 €	59.50 €	53.50 €	47.50 €
Weekly cost for joint management of all parts [$\frac{\text{€}}{\text{week}}$]	44.60 €	60.50 €	54.60 €	48.60 €	42.70 €
Cost variation between individual and joint management of all parts	-51.10%	-7.50%	-8.20%	-9.20%	-10.10%
CM vs AM for individual management of parts	/	-28.30%	-34.70%	-41.30%	-47.90%
CM vs AM for the joint management of all parts	/	35.60%	22.40%	9.0 %	-4.30%

With this cost reduction, individual AM management becomes 47.90% less expensive than individual CM management, and joint AM management becomes 4.30% less expensive than joint CM management, as shown in Table 1. This advantage extends across all hierarchy levels, as depicted in Figure 4, and is consistent also for the hierarchies constructed using the Jaccard index calculated with both single and complete linkage methods, although these results are not explicitly presented here. Our analysis reveals that AM is already a cost-effective solution for the individual management of parts, although the joint management of parts using CM remains 31.8% less expensive at present. However, with expected reductions in printing costs, AM is likely to emerge as the most advantageous option for joint management as well. This highlights the growing potential of AM to become the preferred approach for spare parts management as production costs continue to decrease.

4. CONCLUSIONS

This study provides a preliminary evaluation of additive manufacturing (AM) and classical manufacturing (CM) for the joint management of spare parts. Using a generated dataset based on real data about the consumption of CM and AM parts, we performed hierarchical clustering for both production modes. For each hierarchy level, we optimized the parameters of the periodic review policy outlined in Moharana and Sarmah (2018). Our findings indicate that AM is particularly effective for the individual management of spare parts, utilizing a "one-for-one" replenishment strategy that significantly lowers holding costs and minimizes downtime risks due to its reduced lead times. In contrast, the joint management of all parts currently favors CM, which achieves considerable cost savings by optimizing inventory levels and revision periods. However, the analysis highlights that with a projected 30% reduction in AM printing costs, AM becomes the most cost-effective option across all hierarchy levels, underscoring its potential to transform spare parts management in the future. Future studies should extend this analysis by leveraging real datasets with varying levels of dispersion in parts failure rates and different AM technologies since here only SLM+P was tested. Additionally, further research should explore the potential of on-demand joint replenishment strategies for parts using AM, which represents a prominent application of AM in spare parts management. Lastly, AM's performance during supply chain disruptions should be investigated to evaluate its resilience and cost-efficiency under conditions of uncertainty.

AKNOWLEDGMENT

Project funded under the National Recovery and Resilience Plan (NRRP), Mission 04 Component 2 Investment 1.5 NextGenerationEU, Call for tender n. 3277, 30 December 2021. Award Number: 0001052, 23 June 2022.

REFERENCES

- Babai, M. Z., Boylan, J. E., & Rostami-Tabar, B. (2021). Demand forecasting in supply chains: a review of aggregation and hierarchical approaches., 60(1), 324–348.
- Boylan, J. E., & Syntetos, A. A. (2010). Spare parts management: A review of forecasting research and extensions. *IMA Journal of Management Mathematics*, 21(3), 227–237.
- Coruzzolo, A. M., Balugani, E., & Gamberini, R. (2022). Spare parts management with Additive Manufacturing (AM): a critical review. *IFAC-PapersOnLine*, 55(10), 1159–1164.
- Dellagi, S., Trabelsi, W., Hajej, Z., & Rezg, N. (2020). Integrated maintenance/spare parts management for manufacturing system according to variable production rate impacting the system degradation. *Concurrent Engineering Research and Applications*, 28(1), 72–84.
- Fung, R. Y. K., Ma, X., & Lau, H. C. W. (2001). (T, S) policy for coordinated inventory replenishment systems under compound Poisson demands. *Production Planning and Control*, 12(6), 575–583.

- Gibson, I., Rosen, D., & Stucker, B. (2015). Additive manufacturing technologies: 3D printing, rapid prototyping, and direct digital manufacturing, second edition. *Additive Manufacturing Technologies: 3D Printing, Rapid Prototyping, and Direct Digital Manufacturing, Second Edition*, 1–498.
- Goyal, S. K., & Satir, A. T. (1989). Joint replenishment inventory control: Deterministic and stochastic models. *European Journal of Operational Research*, 38(1), 2–13.
- Heinen, J. J., & Hoberg, K. (2019). Assessing the potential of additive manufacturing for the provision of spare parts. *Journal of Operations Management*, 65(8), 810–826.
- Holmström, J., Partanen, J., Tuomi, J., & Walter, M. (2010). Rapid manufacturing in the spare parts supply chain: Alternative approaches to capacity deployment. *Journal of Manufacturing Technology Management*, 21(6), 687–697.
- Khajavi, S. H., Partanen, J., & Holmström, J. (2014). Additive manufacturing in the spare parts supply chain. *Computers in Industry*, 65(1), 50–63.
- Knofius, N., van der Heijden, M. C., Sleptchenko, A., & Zijm, W. H. M. (2021). Improving effectiveness of spare parts supply by additive manufacturing as dual sourcing option. In *OR Spectrum (Vol. 43, Issue 1)*. Springer Berlin Heidelberg.
- Knofius, N., van der Heijden, M. C., & Zijm, W. H. M. (2019). Moving to additive manufacturing for spare parts supply. *Computers in Industry*, 113, 103134.
- Kulshrestha, N., Agrawal, S., & Shree, D. (2024). Spare parts management in industry 4.0 era: a literature review. *Journal of Quality in Maintenance Engineering*, 30(1), 248–283.
- Li, L., & Schmidt, C. P. (2020). A Stochastic Joint Replenishment Problem with Dissimilar Items. *Decision Sciences*, 51(5), 1159–1201.
- Li, Y., Jia, G., Cheng, Y., & Hu, Y. (2016). Additive manufacturing technology in spare parts supply chain: a comparative study. *International Journal of Production Research*, 55(5), 1498–1515.
- Li, Y., Jia, G., Cheng, Y., & Hu, Y. (2017). Additive manufacturing technology in spare parts supply chain: a comparative study. *International Journal of Production Research*, 55(5), 1498–1515.
- Liu, P., Huang, S. H., Mokasdar, A., Zhou, H., & Hou, L. (2014). The impact of additive manufacturing in the aircraft spare parts supply chain: Supply chain operation reference (scor) model based analysis. *Production Planning and Control*, 1169–1181.
- Liu, S., & Shin, Y. C. (2019). Additive manufacturing of Ti6Al4V alloy: A review. *Materials & Design*, 164, 107552.
- Lolli, F., Coruzzolo, A. M., Peron, M., & Sgarbossa, F. (2024). Insourcing additive manufacturing for spare parts production: is it profitable? An extensive analysis and the proposal of a Decision Support System. *International Journal of Production Research*, 1–21.
- Magazine Additive Manufacturing. (2023). How Am Is Changing Aerospace the Magazine for the Metal Additive Manufacturing Industry Metal Am. www.metal-am.com
- Mecheter, A., Pokharel, S., Tarlochan, F., & Tsumori, F. (2024). A multi-period multiple parts mixed integer linear programming model for AM adoption in the spare parts supply Chain. *International Journal of Computer Integrated Manufacturing*, 37(5), 550–571.
- Mecheter, A., Tarlochan, F., & Kucukvar, M. (2023). A Review of Conventional versus Additive Manufacturing for Metals: Life-Cycle Environmental and Economic Analysis. *Sustainability (Switzerland)*, 15(16), 12299.
- Moharana, U. C., & Sarmah, S. P. (2018). Joint replenishment of associated spare parts using clustering approach. *International Journal of Advanced Manufacturing Technology*, 94(5–8), 2535–2549.
- Peron, M., Coruzzolo, A. M., Basten, R., Knofius, N., Lolli, F., & Sgarbossa, F. (2024). Choosing between additive and conventional manufacturing of spare parts: On the impact of failure rate uncertainties and the tools to reduce them. *International Journal of Production Economics*, 278, 109438.
- Pinçe, Ç., Turrini, L., & Meissner, J. (2021). Intermittent demand forecasting for spare parts: A Critical review. *Omega*, 105, 102513.
- Regis, M., Marin, E., Fedrizzi, L., & Pressacco, M. (2015). Additive manufacturing of Trabecular Titanium orthopedic implants. *Undefined*, 40(2), 137–144.
- Rempala, R. (2003). Joint replenishment multiproduct inventory problem with continuous production and discrete demands. *International Journal of Production Economics*, 81–82, 495–511.
- Roorkhosh, P., Pooya, A., Soleimani Fard, O., & Bagheri, R. (2024). Designing a changeable multi-level supply chain network with additive manufacturing capability and costs uncertainty: a Monte Carlo approach. *Operational Research*, 24(1), 1–37.
- Sgarbossa, F., Peron, M., Lolli, F., & Balugani, E. (2021). Conventional or additive manufacturing for spare parts management: An extensive comparison for Poisson demand. *International Journal of Production Economics*, 233(June 2020), 107993.
- Song, J. S., & Zhang, Y. (2020). Stock or print? impact of 3-d printing on spare parts logistics. *Management Science*, 66(9), 3860–3878.
- Westerweel, B., Basten, R., den Boer, J., & van Houtum, G. J. (2021). Printing Spare Parts at Remote Locations: Fulfilling the Promise of Additive Manufacturing. *Production and Operations Management*, 30(6), 1615–1632.
- Westerweel, B., Basten, R. J. I., & van Houtum, G. J. (2018). Traditional or Additive Manufacturing? Assessing Component Design Options through Lifecycle Cost Analysis. *European Journal of Operational Research*, 270(2), 570–585.
- Wong, K. V., & Hernandez, A. (2012). A Review of Additive Manufacturing. *ISRN Mechanical Engineering*, 2012, 1–10.
- Zhang, Y., Jedeck, S., Yang, L., & Bai, L. (2019). Modeling and analysis of the on-demand spare parts supply using additive manufacturing. *Rapid Prototyping Journal*, 25(3), 473–487.