Alessandra Cantini

Reviewing the configuration of spare parts supply chains considering stock deployment and manufacturing options

PhD research carried out in a cotutelle between the University of Florence (UNIFI) and the Norwegian University of Science and Technology (NTNU)

Thesis for the degree of Philosophiae Doctor

Trondheim, MARCH 2023

Norwegian University of Science and Technology
Faculty of Engineering
Department of Mechanical and Industrial Engineering

NTNU

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ISBN 978-82-326-6211-1 (printed ver.)
ISBN 978-82-326-6108-4 (electronic ver.)
ISSN 1503-8181 (printed ver.)
ISSN 2703-8084 (electronic ver.)

Doctoral theses at NTNU, 2023:49

PRINTED IN NORWAY
NO - 1598

NORDIC SWAN ECOLABEL
Printed matter
2041 0731

Printed by Skipnes Kommunikasjon AS

PHD GRADUATION IN INDUSTRIAL ENGINEERING, CURRICULUM INDUSTRIAL AND RELIABILITY ENGINEERING

CYCLE XXXV

PHD COORDINATOR
Prof. Giovanni Ferrara

Disciplinary Scientific Sector ING-IND/17

PHD GRADUATION IN ENGINEERING, PRODUCTION MANAGEMENT

SENIOR EXECUTIVE OFFICER
Elin Kristidatter Steen

This PhD research was carried out in accordance with the cotutelle agreement between UNIFI and NTNU

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Acknowledgements

I owe my utmost gratitude to my supervisors, Professor Filippo De Carlo, Professor Mirco Peron, and Professor Fabio Sgarbossa. They gave me the opportunity to perform a Ph.D. in co-tutelle between the University of Florence (UNIFI) and the Norwegian University of Science and Technologies (NTNU). I was very lucky since they supported my work with great encouragement, and fruitful discussions. I thank them not only for allowing me to study innovative and interesting research topics, but also for giving me the opportunity to live in Norway, facing an unforgettable life experience that changed me forever.

Special thanks go to Professor De Carlo, without whom this journey would have never started. Thank you for believing in my potential six years ago and thank you for all the precious advice and teachings you have given me during these years. They were essential to grow both professionally and personally.

Furthermore, I would like to thank UNIFI and NTNU for financing and supporting my research study. Thanks for introducing me to the “world” of academy and scientific research. Getting involved in teaching and developing scientific projects and collaborations has been stimulating and very formative. Thanks also for providing me with resources and opportunities to leave a personal mark on the international community by publishing scientific documents.

During this Ph.D. study, I have had the best colleagues one could hope for. Leonardo, Saverio, and Sara thank you for being good office mates, but most importantly, good friends. Mirco, Simone, Nicolo’, Vivek, Mina, Cosmin, Swapnil, Jo, Aili, and Marco thank you all for the time spent together in Trondheim. I have collected so many lovely memories that I will never forget. Thanks also to Ronja and Martina, who are not colleagues but special friends. Your company has radically changed my perception of Trondheim and life outside Italy. I left a piece of my heart with you on the Kristiansten Fortress toboggan run.

Last, but not least, I would like to express my profound gratitude to Marco, my mum, my dad, and my sister. I dedicate this thesis to you. Thank you for all your love and support throughout this hard journey.

Florence (Italy), October 2022

Alessandra Cantini

Summary

Spare parts are strategic assets to ensure the execution of maintenance activities in industrial plants. They are exchangeable parts that can be used to replace damaged components, facilitating the restoration of the functioning of plants and equipment (Huiskonen, 2001; Tapia-Ubeda et al., 2020). Due to the significant role of spare parts, the scientific literature (Frazzon et al., 2016) has emphasized how crucial it is for spare parts retailers to ensure efficient supply chains (SCs), where the right spare parts are stored and delivered in the right place (close to the damaged plant or equipment) at the right time (breakdown time). Aligning spare parts deployment and delivery activities with customer needs leads to customer satisfaction, increased sales profits, greater sustainability, and efficient company performance (Giannikas et al., 2019). Based on this, a well-configured spare parts SC has been recognised as an ever-growing crucial aspect for the success and competitiveness of spare parts retailers (Esmaeili et al., 2021).

Among the decisions that impact the configuration of spare parts SCs, stock deployment is of primary importance (Gregersen and Hansen, 2018). Antithetical stock deployment policies can be selected, such as inventory centralisation, decentralisation, or hybrid stock deployment policies, which imply countervailing advantages in terms of SC flexibility and responsiveness, delivery time, inventory levels, mitigation of demand uncertainty, facility management efforts, and number of supply orders to replenish distribution centres (DCs). Due to the opposite advantages of inventory centralisation and decentralisation and the typical volatility of spare parts demand, determining optimal stock deployment policies has been recognised as a challenging task worldwide (Basto et al., 2019; Vlajic et al., 2012), where the main issue is to minimise inventory costs while guaranteeing high service levels (Jiang et al., 2019). In the case of spare parts, the optimisation of stock deployment policies and the consequent configuration of SCs are further hampered by two main issues. First, the optimal stock deployment policies of spare parts should not be defined only once (when the business is founded) but should be regularly reviewed during the business lifetime, adapting to fluctuations in customer needs and spare parts criticality and, consequently, reviewing the SC configuration (Alfieri et al., 2017; Del Prete and Primo, 2021). Second, the optimal manufacturing technology should be selected for each stock keeping unit (SKU), opting for conventional (CM) or additive manufacturing (AM), where AM is considered the next revolution in the field of spare parts, allowing to disrupt the choice between inventory centralisation and decentralisation (Xu et al., 2021).

Despite the achievable benefits of optimising the configuration of spare parts SCs, the choice between inventory centralisation and decentralisation is not the subject of much scientific research. It is also unclear what the optimal manufacturing technology is for spare parts (CM or AM) and how different

manufacturing technologies impact the choice of optimal stock deployment policies (Frandsen et al., 2020; Trancoso et al., 2018). Moreover, the scientific literature has recently underlined the lack of structured methodologies (especially heuristic ones) to review the configuration of spare parts SCs, aligning stock deployment policies and spare parts manufacturing technology to demand fluctuations (Eldem et al., 2022). In this context, the present research aims to fill this gap by supporting and creating new knowledge for researchers and practitioners (spare parts retailers) on how to review the configuration of spare parts SCs, focusing on optimising the stock deployment policies and manufacturing technology of spare parts. To this end, we began the current research by developing a systematic literature network analysis (SLNA) on the topic of spare parts deployment in SC configuration and the choice between inventory centralisation and decentralisation. The SLNA combines a typical systematic literature review (SLR) with an analysis of quantitative information emerging from bibliographic networks. Therefore, the SLNA allowed us to understand the extant body of knowledge in the analysed domain, confirming the aforementioned literature gaps, laying the foundation for future research investigations, and providing an answer to the following research question.

- **RQ1:** What are the extant literature and driving research streams on the topic of stock deployment in spare parts SCs?

Based on the identified literature gap and future research opportunities, two additional research questions were derived:

- **RQ2:** What viable heuristic methodologies can be proposed to review stock deployment policies in spare parts SCs?
- **RQ3:** What is the optimal manufacturing technology for spare parts in SCs with different stock deployment policies?

To answer the above research questions, the following research methods were applied:

- **RQ1:** SLNA
- **RQ2:** mathematical modelling, case study research, and experimental research
- **RQ3:** mathematical modelling and experimental research

By answering each research question, the following outcomes were achieved:

- **RQ1:** An SLNA of the scientific literature on the topic of inventory centralisation/decentralisation and stock deployment in spare parts SCs:
    - Identification of the extant literature on the analysed topic;

    - Investigation of past and current research themes related to the considered topic, determining the driving research streams, which mainly concur in developing the literature on this field.
- **RQ2 and RQ3:** Three novel heuristic methodologies for reviewing the configuration of spare parts SCs:
    - Proposal of a data-driven heuristic methodology (based on a multicriteria ABC criticality classification) to review the stock deployment policies in spare parts SCs without considering the spare parts manufacturing technology **(answers RQ2)**;
    - Proposal of a DSS to compare the cost-effectiveness of centralised and decentralised SCs, where spare parts can be purchased from suppliers as AM or CM parts and the optimal manufacturing technology is selected **(answers both RQ2 and RQ3)**;
    - Proposal of a DSS to compare the cost-effectiveness of centralised and decentralised SCs, where spare parts can be purchased from suppliers as CM parts or produced in-house as AM parts and the optimal manufacturing technology is selected **(answers both RQ2 and RQ3)**;

Overall, the main goal of this research work was achieved by providing support and new knowledge to researchers and practitioners (spare parts retailers) on how to review the configuration of spare parts SCs, focusing on optimising stock deployment policies and spare parts manufacturing technologies. Specifically, the answer to RQ1 highlights the current body of knowledge in the analysed domain, remarking on possible research opportunities. Then, the answers to RQ2 and RQ3 provide spare parts retailers with heuristic methodologies and DSSs to recurrently review the configuration of spare parts SCs, defining the optimal stock deployment policies with AM or CM spare parts.

Abbreviations

AM – Additive Manufacturing

CAD – Computer-Aided Design

CM – Conventional Manufacturing

CPP – Citations Per Publications

DC – Distribution Centre

DSS – Decision Support System

KPIs – Key performance indicators

NTNU – Norwegian University of Science and Technology

RQ – Research Question

SC – Supply Chain

SKU – Stock Keeping Unit

SLNA – Systematic Literature Network Analysis

SLR – Systematic Literature Review

UNIFI - University of Florence

Preface

Before consulting this thesis, the reader needs to be familiar with some key concepts and terms, which are clarified in this section.

The fulcrum of this thesis is **spare parts retailers**, namely aftersales service distributors, who procure spare parts from suppliers and deliver them to customers based on their demand (Daskin et al., 2002). Spare parts demand depends on the maintenance activities to be performed by customers on plants or equipment. Customers (as well as suppliers) may be both internal and external, depending on whether they work in the same company as the spare parts retailers. For example, assuming that a spare parts retailer also provides a public transport service, if he delivers spare parts to carry out maintenance activities on his own vehicles, then he targets an internal customer; however, if he delivers spare parts to maintain other vehicles (not his property), then he targets an external customer. Since all investigations conducted in this thesis are aimed at optimising the performance of spare parts retailers (considering their viewpoint, not that of suppliers or customers), we refer to **spare parts supply chains (SCs)**, addressing those SCs that include only logistic activities managed by spare parts retailers, namely spare parts procurement and delivery (Tapia-Ubeda et al., 2020). Specifically, two-echelon SCs are considered, where, in the first echelon, spare parts are procured from suppliers and stored inside distribution centres (DCs), and in the second echelon, spare parts are delivered to customers. No other upstream or downstream echelons were considered for two reasons. First, other activities, such as spare parts production, are not usually in charge of spare parts retailers (unless they are performed inside DCs, and in that case, they are investigated). Second, no generality is lost by considering two-echelon SCs, since they can easily be extended into multi-echelon SCs if the supplier of one echelon is considered the customer of the previous one (Ding and Kaminsky, 2018). Section 2.1 provides detailed information on the SC structure considered. However, as mentioned above, the focal point of this thesis is **existing spare parts SCs**, for which we investigate how to review the configuration. This means that SCs are considered where the echelons, the DCs in each echelon, and the procurement/delivery modalities have been set up by spare parts retailers since they have already established their business. However, the aim is to review the SC configuration over time to optimise logistics activities and keep them aligned with customer demand.

Lastly, it is worth reporting a semantic clarification. In this thesis, the terms **"manufacturing technology"** and **"manufacturing option"** are used as synonyms, referring to how spare parts were produced (before being procured and delivered by retailers) and opting for additive (AM) or conventional (CM) manufacturing.

List of Appended Papers and Declaration of Authorship

Paper	Title	Declaration of authorship
1	Cantini, A., Ferraro S., Leoni L., and Tucci M., 2022. Inventory centralization and decentralization in spare parts supply chain configuration: a bibliometric review. Proceedings of the Summer School Francesco Turco.	Cantini conceptualised the paper and conducted the systematic literature network analysis. Cantini wrote the paper with feedback from Ferraro, Leoni, and Tucci.
2	Cantini, A., Peron, M., De Carlo, F., and Sgarbossa, F., 2022. A data-driven methodology for the dynamic review of spare parts supply chain configuration. International Journal of Production Research (currently under review). *This paper originates as an extended version of the paper "Cantini, A., De Carlo, F., Leoni, L., Tucci, M., 2021. A novel approach for spare parts dynamic deployment", which has been* ***published*** *at the "Proceedings of the Summer School Francesco Turco" and* ***awarded with the "Best Paper Award"****. However, the awarded paper (short version) is not appended to this thesis since its content is entirely included and properly extended in the above paper (extended version). Therefore, the authors consider redundant its consultation.*	Cantini conceptualised the paper and developed the data-driven methodology. Cantini wrote the paper with feedback from Peron, De Carlo, and Sgarbossa.
3	Cantini, A., Peron, M., De Carlo, F., Sgarbossa, F., 2022. A decision support system for configuring spare parts supply chains considering different manufacturing technologies. International Journal of Production Research 0, 1-21. doi: 10.1080/00207543.2022.2041757	Cantini conceptualised the paper and developed the decision support system. Cantini wrote the paper with feedback from Peron, De Carlo, and Sgarbossa.
4	Cantini, A., Peron, M., De Carlo, F., and Sgarbossa, F., 2022. On the impact of additive manufacturing on the review of spare parts supply chains configuration: a decision support system. International Journal of Production Research (currently under review).	Cantini conceptualised the paper and developed the decision support system. Cantini wrote the paper with feedback from Peron, De Carlo, and Sgarbossa.

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Part I: Main report

1. Introduction

This section discusses the context and motivation for the current research study. First, a general background is introduced to familiarise readers with the terms and topics investigated throughout the rest of the study. Next, the motivation for conducting the research study is explained. Subsequently, the scope of this research study is clarified, defining the research questions and objectives of the study. Finally, the outline of the whole study is described, summarising the content of each section to guide readers who may be interested in consulting only specific parts of this work.

1.1. Background

As strategic assets that ensure the execution of maintenance activities in companies, spare parts are exchangeable parts suitable for replacing damaged components and restoring the functioning of plants and equipment (Huiskonen, 2001). Hence, their availability is fundamental for reducing breakdown times and their consequent negative effects at both the operational and economic levels. Given the key role of spare parts, the scientific literature (Frazzon et al., 2016) has emphasised the need to optimally configure spare parts supply chains (SCs), enabling spare parts retailers to store and deliver the right Stock Keeping Units (SKUs) in the right place (close to the damaged plant or equipment) at the right time (breakdown time). However, optimally configuring spare parts SCs is not an easy task for four main reasons. First, many interrelated decisions have to be made (e.g., how many DCs to set up, where to geographically locate them, and how to replenish each DC), and changes in one of these decisions influence the others (Fathi et al., 2021; Jiang and Nee, 2013). Second, while an unavailability of spare parts (inventory stock-out) leads to customer dissatisfaction, filling distribution centres (DCs) with excessive inventories causes high administrative costs for spare parts retailers, as well as opportunity costs related to bad investments in resources (Stoll et al., 2015). Therefore, spare parts retailers should search for a trade-off between reduced inventories and high service levels (Esmaeili et al., 2021). Third, specific features hinder the configuration of spare parts SCs compared to other items (e.g., productive supplies, raw materials, or commodities), such as the unpredictability of demand and high expected service levels (Tapia-Ubeda et al., 2020). Finally, due to the variability of spare parts demand, if spare parts retailers want to remain competitive in the market, they cannot define the SC configuration only once (when the business is founded); rather, they must review the configuration of existing SCs during the whole business lifetime, adapting to fluctuations in customer needs and changes in spare parts criticality (Alfieri et al., 2017; Del Prete and Primo, 2021).

Despite the aforementioned difficulties, optimising the configuration of a spare parts SC and reviewing this optimisation over time provides multiple benefits for spare parts retailers, including high customer satisfaction (due to the availability of spare parts in DCs), increased sales profits, greater SC sustainability, and higher SC performance (Giannikas et al., 2019). For this reason, to ensure the success of spare parts retailers, it is essential to adopt structured methodologies for configuring and reviewing the configuration of spare parts SCs. However, while some literature studies have examined how to configure spare parts SCs for the first time (when the business is founded), the problem of reviewing the configuration of existing SCs has been overlooked (Del Prete and Primo, 2021; Eldem et al., 2022). As a result, due to the lack of structured methodologies to review the configuration of spare parts SCs, many spare parts retailers choose the SC configuration only one time and never question it (Hu et al., 2018).

Among the decisions that affect the review of an existing spare parts SC configuration, associating optimal stock deployment policies with individual SKUs has been recognised as of primary importance (Basto et al., 2019; Gregersen and Hansen, 2018; Vlajic et al., 2012). Choosing stock deployment policies implies defining (each time the SC configuration is reviewed) how to allocate stocks of spare parts inside DCs and opting for antithetical strategies, such as inventory centralisation, decentralisation, or hybrid stock deployment policies (Pour et al., 2016). These alternatives differ based on the so-called "degree of inventory centralisation" (also known as the "degree of inventory-pooling"), where inventory pooling is the practice of using a common pool of stocks to satisfy the random demand accumulated from two or more customers (Wang and Yue, 2015). In centralisation, the maximum degree of inventory centralisation is achieved. All SKUs are stored in a single central DC, which is tasked with serving the demand of all customers (Milewski, 2020). The advantages of centralisation include mitigating demand uncertainty and minimising inventory levels (due to the well-known risk-pooling effect), a low number of supply orders to replenish DCs, and reduced facility management efforts (a single DC is set, and few or no duplications of equipment and staff are required), but it implies high delivery times along with reduced SC flexibility and responsiveness (Wanke and Saliby, 2009). Conversely, in decentralisation, a minimum degree of inventory centralisation is achieved. In fact, multiple independent DCs are set, each storing SKUs to meet the demand of a specific local customer (Alvarez and van der Heijden, 2014). This stock deployment policy is suggested when the SC implies delivering spare parts to many customers spread over a large area (Daskin et al., 2002). This SC configuration has countervailing advantages to centralisation, including high SC flexibility and responsiveness, as well as reduced delivery times, but it loses the advantages related to risk-pooling and thus entails no mitigation of demand uncertainty and high inventory levels. Decentralisation also faces a high number of supply orders and requires high facility management efforts since multiple DCs are set (Holmström et al., 2010). Finally, in hybrid stock deployment policies, an intermediate degree of inventory centralisation is achieved since an intermediate number of DCs is selected between that of centralisation (one) and that of decentralisation (one per each local customer), tasking each DC with filling the demand of some customers (partial aggregation), and thus achieving trade-off advantages between centralisation and decentralisation (Cavalieri et al., 2008). Figure 1 summarises the pros and cons of different stock deployment policies.

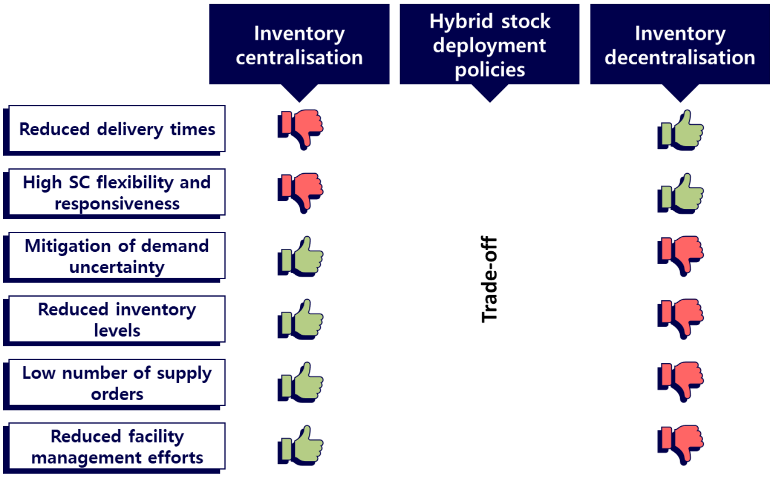

Figure 1. Advantages and disadvantages of different stock deployment policies.

Given the contrasting advantages of inventory centralisation and decentralisation, reviewing the SC configuration by focusing on optimising stock deployment policies has been recognised as a challenging but strategic opportunity for spare parts retailers (Cohen et al., 2006; Milewski, 2020). In fact, it has been proven that maintaining the optimisation of stock deployment policies during the business lifetime enables spare parts retailers to control inventory investments (which typically represent 20% to 60% of the company's balance sheet assets), cut unnecessary SC costs, obtain a customer-centred aftersales service, and meet pre-determined service levels, which is essential for building up customer loyalty and the success of spare parts retailers (Manikas et al., 2019; Singh, 2006). Despite the benefits achievable by optimising stock deployment policies (thus reviewing the SC configuration), little research has focused on the choice between inventory centralisation, decentralisation, and hybrid stock deployment policies in spare parts SCs (Graves and Willems, 2005; Zijm et al., 2019). Therefore, nowadays, many spare parts retailers struggle to find structured methodologies to cope with this issue (Avventuroso et al., 2018; Khajavi et al., 2014).

This literature gap has recently been exacerbated by another aspect. Additive manufacturing (AM) has been underlined as an emerging technology, that disrupts the choice of optimal stock deployment policies and the consequent review of spare parts SC configurations (Xu et al., 2021). Unlike conventional manufacturing (CM), AM enables more flexible and responsive SCs, where the spare parts production can be moved closer to the end customer (achieving an "in-house" production by installing 3D printers directly into DCs), consequently reducing the dependency on suppliers, the procurement lead times, and the inventory levels (Mashhadi et al., 2015; Waterman and Dickens, 1994). These AM abilities revolutionise the characteristics of inventory centralisation, decentralisation, and hybrid stock deployment policies. For this reason, when reviewing the configuration of spare parts SCs, spare parts retailers also have to decide on the manufacturing technology to adopt for each SKU (AM or CM), since this choice affects decisions on stock deployment policies (Ahmed et al., 2022; Chaudhuri et al., 2021). However, the scientific literature lacks structured methodologies for comparing different manufacturing technologies (Knofius et al., 2021). Therefore, the convenience of performing a switchover from CM to AM spare parts cannot be established, and the potential for success of spare parts retailers is limited. Because SKUs cannot be associated with preferable manufacturing technology, the selection of optimal stock deployment policies is hampered, which prevents an adequate review of the spare parts SC configuration (Frandsen et al., 2020; Trancoso et al., 2018).

To fill the identified gaps, this study investigates the topic of reviewing the configuration of spare parts SCs, focusing on optimising stock deployment policies and considering different spare parts manufacturing technologies. In this domain area, research activities were carried out to support and create new knowledge for researchers and practitioners (spare parts retailers) in two main ways. First, by examining and reorganising the extant literature through a systematic literature network analysis (SLNA), we confirm the literature gaps, and we identify the driving research streams, laying the foundation for future research opportunities. Second, by providing novel heuristic methodologies and decision support systems (DSSs) that spare parts retailers can use to understand how to review and optimise stock deployment policies of spare parts with different manufacturing technologies.

1.2. Research motivation

This research project originates from a specific request for support made by two companies working in the field of spare parts retail (one from southern Europe and the other from northern Europe). Both companies identified as a key element for their success the optimisation of spare parts SC configurations, with a specific emphasis on optimising stock deployment policies (i.e., opting for inventory centralisation, decentralisation, or hybrid stock deployment policies). Due to the typical volatility of spare parts demand, the two companies underlined the importance of continuously reviewing the stock deployment policies (and the consequent SC configuration) during the business lifetime, aligning them with ever-changing customer needs and spare parts criticality. However, company managers revealed a strong difficulty in doing so, pointing out the lack of quick and easy-to-use (but reliable and structured) literature methodologies for reviewing stock deployment policies in spare parts SCs.

This gap was first highlighted by company managers and then confirmed by consulting the scientific literature. Based on a preliminary literature review on the topic of spare parts deployment, we determined that an optimal SC configuration is essential for the success of spare parts retailers (Cohen et al., 2006; Yazdekhasti et al., 2022). Among the decisions that impact the configuration of spare parts SC, stock deployment policies are of paramount importance (Stoll et al., 2015). However, stock deployment policies cannot be chosen only once (when the business is founded); rather, they must be reviewed over time to follow changes in spare parts demand and lead to higher customer satisfaction and company competitiveness (Del Prete and Primo, 2021). For this reason, it is important to seek quick and easy-to-use (but reliable and structured) methodologies that allow for the continuous review of stock deployment policies in spare parts SC (Manikas et al., 2019; Sheikhar and Matai, 2022). In particular, to provide spare parts retailers with practical solutions applicable in real companies, heuristic optimisation methodologies should be developed that show the potential for success, converging to optimal solutions without requiring the application of high computing resources and advanced technologies (which are still lacking in many real companies) (Basto et al., 2019). However, the extant scientific literature neglects not only heuristic methodologies but, more generally, any methodologies for reviewing stock deployment policies in spare parts SCs (Gregersen and Hansen, 2018; Milewski, 2020). Therefore, stemming from both industrial and theoretical motivations, this research project was developed to fill the identified gap and create new knowledge (as well as quick and easy-to-use heuristic methodologies) to review stock deployment policies in spare parts SCs.

Through our investigations of how to review stock deployment policies in spare parts SCs, and consulting both companies and the scientific literature, another issue emerged that further motivated this research study. AM is an emerging manufacturing technology that shows great differences from CM, offering the opportunity to revolutionise the configuration of spare parts SCs (Frandsen et al., 2020). Due to the distinct impacts of AM and CM on the characteristics of spare parts SCs, optimal stock deployment policies should be selected depending on many factors, including spare parts manufacturing technology. However, there are no clear indications (neither in the literature nor in industrial contexts) of the optimal manufacturing technology to adopt for spare parts or how AM and CM impact the configuration of spare parts SCs (Khajavi et al., 2014; Xu et al., 2021). Hence, further studies are required to encourage the correct introduction of AM in companies, thus reviewing the stock deployment policies to establish not only whether it is more convenient to opt for inventory centralisation, decentralisation, or hybrid stock deployment policies but also whether the selected alternative should be applied to CM or AM spare parts. This need additionally motivated the present research study, where we explore how to review the configuration of spare parts SCs, focusing on optimising stock deployment policies and considering different manufacturing options.

1.3. Research scope

The current research study lies within the research area of reviewing the spare parts SC configuration. Specifically, the focus is on the domain of stock deployment optimisation (i.e., the choice of inventory centralisation, decentralisation, or hybrid stock deployment policies).

As aforementioned, many decisions affect the spare parts SC configuration. Among these decisions, one of the fundamentals is the stock deployment policies associated with individual SKUs, opting for inventory centralisation, decentralisation, or hybrid stock deployment policies. Since the demand for spare parts is typically volatile and unpredictable, stock deployment policies should be continuously reviewed during the business lifetime, adapting to fluctuations in customer needs and spare parts criticality. Hence, seeking to improve customer satisfaction and enable the success of spare parts retailers, the scope of this project is to investigate how to review and optimise stock deployment policies in spare parts SCs.

Given the recent development of AM as a successful manufacturing technology in the field of spare parts, spare parts retailers have shown a strong interest in investigating the impacts of AM on SC configuration and comparing its advantages over CM. Based on this interest, willing to create new (useful) knowledge for both researchers and practitioners (spare parts retailers), in this research study, we decided to investigate how to optimise stock deployment policies not only by evaluating the benefits of different degrees of inventory centralisation (centralisation, decentralisation, or hybrid stock deployment policies), but also by considering different manufacturing technologies (AM and CM).

1.4. Research questions and objectives

Motivated by the challenges and research problem explained in Section 1.2, and pursuing the research scope outlined in Section 1.3, the aim of the current study can be summarised as follows:

- To support and create new knowledge for researchers and practitioners (spare parts retailers) on how to review the configuration of spare parts SCs, focusing on optimising stock deployment policies and considering different manufacturing options.

To achieve this aim, the first goal was to understand the state-of-the-art literature on the topic of stock deployment in spare parts SCs, thus identifying the driving research streams that mainly concur in developing the literature in this field. To this end, we performed an SLNA to answer the following research question:

- **RQ1:** What are the extant literature and driving research streams on the topic of stock deployment in spare parts SCs?

Besides understanding the current body of knowledge in the considered topic, we identified three driving research streams from the SLNA: the optimisation of stock deployment in SCs with AM spare parts, the optimisation of stock deployment in closed loop SCs, and the use of heuristic optimisation methodologies to review stock deployment policies in spare parts SCs. Since there was no time to explore all these possible research opportunities, according to the request for support received by real companies (already explained in Section 1.2) and considering the literature gaps highlighted by them, we decided to limit the objectives of this study. Specifically, we focused on providing new insights into the following:

- The use of heuristic optimisation methodologies to review stock deployment policies in spare parts SCs.
- The optimisation of stock deployment in SCs with AM spare parts. Here, we investigated the impact of AM on the configuration of spare parts SCs, comparing AM with CM, and determining the optimal spare parts manufacturing technology in SCs with different stock deployment policies.

From these research objectives, two additional research questions were derived, that guided the next research process:

- **RQ2:** What viable heuristic methodologies can be proposed to review stock deployment policies in spare parts SCs?

Owing to the typical volatility of spare parts demand, spare parts retailers should not plan the stock deployment policies of individual SKUs only once (when the business is founded). Rather, they should review them during the business lifetime and align them (and the consequent SC configuration) with changes in customer needs and spare parts criticality.

The review of stock deployment policies should not be made randomly, but should be based on structured methodologies that indicate the optimal alternative between inventory centralisation, decentralisation, or hybrid stock deployment policies, aiming to reduce logistic costs while ensuring a high service level. Specifically, as emerged in the SLNA, heuristic optimisation methodologies should be preferred to provide spare parts retailers with quick and easy-to-use methodologies applicable in real companies without requiring high computational resources and advanced technologies. However, the extant literature overlooks heuristic methodologies of this type, and the topic of reviewing stock deployment policies in spare parts SCs has not been sufficiently explored. Therefore, the second research question aims to develop and propose novel heuristic methodologies to review and optimise stock deployment policies in spare parts SCs.

- **RQ3:** What is the optimal manufacturing technology for spare parts in SCs with different stock deployment policies?

The review of stock deployment policies in spare parts SCs is further complicated because AM is an emerging manufacturing technology that shows great differences from CM, thus offering the opportunity to revolutionise the characteristics of spare parts SCs. Because of the distinct impacts that AM and CM have on the characteristics of spare parts SCs, the optimal choice between inventory centralisation, decentralisation, and hybrid stock deployment policies should also be made a function of the manufacturing technology selected for spare parts. For this reason, nowadays, spare parts retailers are interested in comparing the impacts of AM and CM on the choice of optimal stock deployment policies and aim to invest in AM technologies if this produces benefits over CM. However, many spare parts retailers are still far from adopting AM technologies in their SCs, since the literature lacks structured methodologies to establish when a switchover from SCs of CM spare parts to AM ones is convenient. Based on this, the third research question aims to provide spare parts retailers with DSSs to compare AM and CM in SCs with different stock deployment policies and to select the optimal alternative. As a result, the two DSSs will guide the rules for choosing between inventory centralisation, decentralisation, or hybrid stock deployment policies and for selecting the optimal manufacturing technology.

1.5. Thesis outline

This thesis is written in the form of a collection of papers. Hence, the thesis outline is divided into two parts. Part I provides the main report, which is based on research that has been carried out and described in the following appended papers. Part II contains a compendium of scientific papers developed on the topic of "reviewing the configuration of spare parts SCs considering stock deployment and manufacturing options".

Part I provides an overview of the research process and synthesises the contributions of the independent appended publications into a coherent argument, thus clarifying their interrelations. Part I is organised as follows.

Section 1 introduces the specific problems investigated and the motivations behind the developed research. Furthermore, Section 1 describes the research questions addressed in this study, and the objectives stated to answer each research question. This section concludes by summarising the scope and structure of the study.

Section 2 presents the theoretical background of the research. It starts by describing how to configure spare parts SCs, explaining their differences with respect to other SCs (of commodities, raw materials, productive supplies, etc.). Next, Section 2 underlines the importance of reviewing the spare parts SC configuration over time, particularly optimising stock deployment policies. Here, the main differences between inventory centralisation, decentralisation, and hybrid stock deployment policies are discussed, reporting their respective advantages and disadvantages. Finally, specific considerations are provided regarding the impact of AM and CM on the characteristics of spare parts SCs, explaining why these differences affect the optimisation of stock deployment policies and spare parts manufacturing technologies.

Section 3 describes the research design by introducing the research methods used to develop this project and by discussing the research quality based on the four accepted requirements.

Section 4 presents and discusses the results and findings of this work, explaining how the key outcomes address the research questions.

Section 5 summarises the research study and provides the final remarks and conclusions. Furthermore, the research limitations are highlighted, and some recommendations for further research are proposed.

Figure 2 provides a schematic representation of the outline of Part I, showing how Sections 1-5 compose the well-known introduction, methods, results, discussion, and conclusion (IMRaD) structure suggested by Cargill and O'Connor (2021).

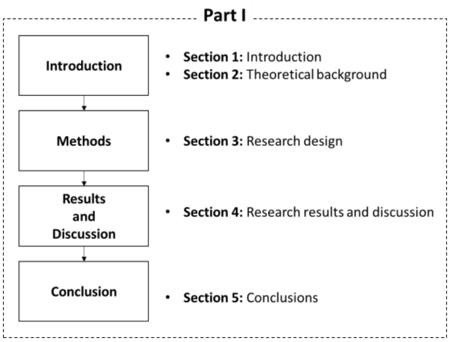

Figure 2. Outline of Part I

Part II contains the collection of papers, which were written to disseminate the results and outcomes of the developed research study. It consists of two published papers (Papers 1 and 3) and two papers that are currently under the review process (Paper 2 and 4):

- **Paper 1:** Cantini, A., Ferraro S., Leoni L., and Tucci M., 2022. Inventory centralization and decentralization in spare parts supply chain configuration: a bibliometric review. Proceedings of the Summer School Francesco Turco.
- **Paper 2:** Cantini, A., Peron, M., De Carlo, F., and Sgarbossa, F., 2022. A data-driven methodology for the dynamic review of spare parts supply chain configuration. International Journal of Production Research (currently under review).

  This paper originates as an extended version of the paper "Cantini, A., De Carlo, F., Leoni, L., Tucci, M., 2021. A novel approach for spare parts dynamic deployment", which has been ***published*** *at the "Proceedings of the Summer School Francesco Turco" and* ***awarded with the "Best Paper Award"****. However, the awarded paper (short version) is not appended to this thesis since its content is entirely included and properly extended in the above paper (extended version). Therefore, the authors consider redundant its consultation.*
- **Paper 3:** Cantini, A., Peron, M., De Carlo, F., Sgarbossa, F., 2022. A decision support system for configuring spare parts supply chains considering different manufacturing technologies. International Journal of Production Research 0, 1-21. doi: 10.1080/00207543.2022.2041757
- **Paper 4:** Cantini, A., Peron, M., De Carlo, F., and Sgarbossa, F., 2022. On the impact of additive manufacturing on the review of spare parts supply chains configuration: a decision support system. International Journal of Production Research (currently under review).

2. Theoretical background

This section provides the theoretical background that frames and supports the current research study. As summarised in Figure 3, Subsection 2.1 presents the general context of the analysis, explaining how to configure spare parts SCs and highlighting the difficulties associated with managing spare parts SCs as opposed to other types of products (e.g., commodities, raw materials, and productive supplies). Having configured spare parts SCs, Subsection 2.2 provides specific explanations on how to review the configuration of existing SCs, reporting on the two main decisions to be made, and why we focus on one of them (i.e., optimising stock deployment policies). Finally, in Subsection 2.3, we describe the impacts of AM and CM on the characteristics of spare parts SCs, explaining why the manufacturing technology selected for spare parts affects the choice of optimal stock deployment policies (and the consequent SC configuration review), which must be optimised.

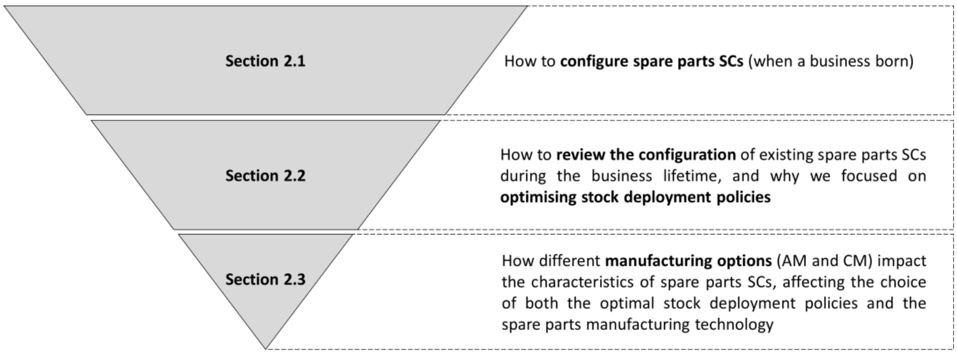

Figure 3. Schematic representation of the content in Section 2

2.1. Configuring spare parts supply chains

An SC is a network of organizations, individuals, activities, information, and resources involved in creating a product or service and delivering it to end-customers (Larson and Rogers, 1998). As defined by Quinn (1997), an SC encompasses all the activities associated with moving goods (and the related information) from the raw materials stage through to the final consumer, including procurement, production scheduling, order processing, storage, inventory management, delivery (transportation), and customer service. Depending on the context, an SC can assume sophisticated and dynamic structures involving multiple suppliers, manufacturers, DCs, and customers. Moreover, the material flow may be in a single direction (from suppliers to customers) or in multiple directions, even including reverse flows, where used products re-enter the SC at any point (Martin et al., 2010). However, as reported by Tapia-Ubeda et al. (2020), when dealing with spare parts SCs, spare parts retailers typically face two-echelon SCs, whose structure (Figure 4) has been described by many authors (Daskin et al., 2002; Huiskonen, 2001; Martin et al., 2010). One or more suppliers serve spare parts to replenish the set of DCs owned by spare parts retailers (first echelon). Then (second echelon), from each DC, spare parts retailers deliver certain stocks to satisfy customer demand at specific consumption points (Alvarez and van der Heijden, 2014). Therefore, in this thesis, we focused on two-echelon spare parts SCs structured as shown in Figure 4, bearing in mind two main considerations. First, the choice of focusing on two-echelon SCs fits with Cohen et al. (1997), who reported that a high number of echelons rarely occur in real spare parts retail companies, indicating that two-echelon SCs are more frequent. Hence, focusing on two-echelon SCs provides spare parts retailers with research study results that are practical and applicable in real companies. Second, no generality is lost by considering two-echelon SCs, since they can easily be extended into multi-echelon SCs if the supplier of one echelon is considered the customer of the previous one (Ding and Kaminsky, 2018).

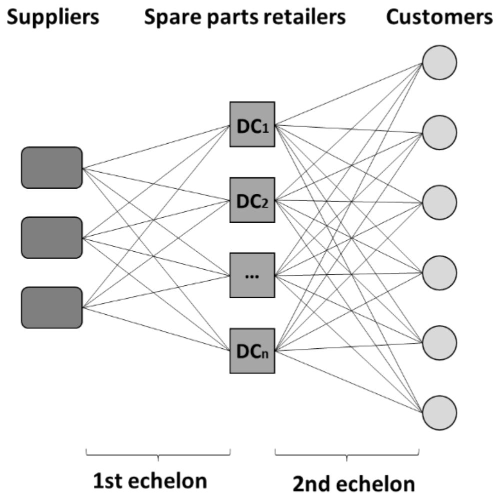

Figure 4. Common structure of a spare parts SC (Tapia-Ubeda et al., 2020)

Besides defining the number of echelons (two, as in Figure 4), configuring a spare parts SC has been defined as an activity to determine the type, size, number, and location of DCs where spare parts are temporarily stocked on their way to the end-customer and define how to procure, store, and deliver spare parts (Mangiaracina et al., 2015). Because of many options to choose from and the high variety of available network alternatives, configuring spare parts SCs is a complex mission that requires adopting structured methodologies for accomplishing three main tasks (Ballou, 1981). The first task is to select the facility design, which involves choosing the number of DCs to be set, the geographical location of each DC, the capacity of each facility, and the stock deployment policies, defining how to allocate customer demand to each DC, and which SKUs to store in each DC (Abrahamsson and Brege, 1997). The second task involves defining the stock supply policies in each DC, which means planning how to replenish inventories, opting for make-to-stock (push) or order-on-demand (pull) policies, and deciding how many stocks to supply and how often (Zhang et al., 2021). Finally, the third task entails designing the delivery mode, which involves selecting the transportation fleet and the customer delivery schedule while seeking to reduce delivery time and minimise transportation costs (Mourits and Evers, 1995). Figure 5 depicts the main decisions that affect an SC configuration.

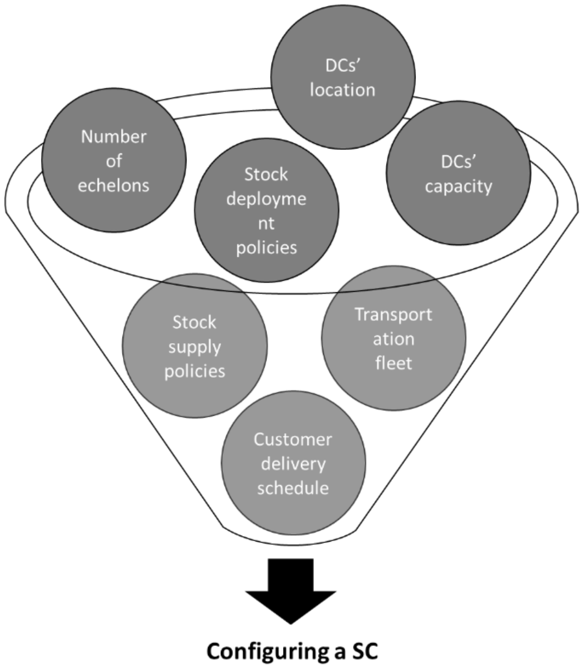

Figure 5. Decisions that impact the configuration of SCs

On top of the difficulties related to the need to accomplish several tasks, another aspect makes the SC configuration process even more complicated. Specific features distinguish spare parts from other products (such as productive supplies, raw materials, or commodities) (Tapia-Ubeda et al., 2020). First, spare parts demand is typically characterised by low volumes and unpredictable behaviour, which is strongly volatile and sporadic (Persson and Saccani, 2007). This erratic demand for spare parts is dictated by customer maintenance policies related to plants or equipment failures that are not always easy to predict. Second, technology and assets advance over the years, and so do their spare parts. Hence, the demand for some SKUs is sometimes met through the cannibalism of other parts, which increases demand uncertainty (Kennedy et al., 2002). Third, service level requirements are usually high, as the effects of spare parts unavailability may be financially remarkable for customers (Cohen and Lee, 1990). Fourth, SKUs managed by spare parts retailers may be numerous and expensive, which, combined with the unpredictability of demand, makes it essential to minimise inventories despite the need to ensure high service levels (Huiskonen, 2001). Finally, spare parts can be produced with different manufacturing technologies (AM and CM), which impact SC characteristics (as later discussed in Section 2.3), resulting in an additional variable to consider in the SC configuration process.

Despite the abovementioned difficulties, optimally configuring spare parts SCs is fundamental, as introduced in Section 1.1. A well-configured SC helps spare parts retailers achieve customer loyalty (Manikas et al., 2019), along with minimising the SC total costs, which include the cost for purchasing spare parts from suppliers (directly related to spare parts production costs), the cost for emitting supply orders to replenish DCs (ordering costs), the cost for keeping stocks in inventory (holding costs), the transportation cost (for delivering spare parts to customers), the fixed cost of facilities, and the backorder cost. Given the significant impacts of a well-configured SC on the performance of spare parts retailers, it is strongly recommended to adopt structured methodologies for optimally configuring SCs (Graves and Willems, 2005; Melo et al., 2009).

2.2. Reviewing the configuration of spare parts supply chains and the issue of optimising stock deployment policies

In addition to highlighting the importance of optimally configuring an SC every time a new business is founded, in Section 1.1, we also pointed out the need to review the configuration of existing spare parts SCs during the business lifetime. According to many authors (Caron and Marchet, 1996; Eldem et al., 2022; Mangiaracina et al., 2015), defining an initial SC configuration with optimal performance is a good starting point, but it is not sufficient to face the volatility of spare parts demand and perpetuate SC optimisation over time.

Therefore, considering an existing SC (where the echelons, the DCs in each echelon, and the transportation fleet are already set), spare parts retailers should regularly review its configuration, perform fine-tuning activities, and maintain an alignment between logistics activities and customer needs. To this end, among the decisions that affect the configuration of spare parts SCs (Figure 5), two are reported to be of primary importance when reviewing the configuration of existing SCs, as depicted in Figure 6 (Manikas et al., 2019): the stock deployment policies and the stock supply policies adopted for individual SKUs. By not adequately reviewing the stock deployment and supply policies over time, variations in spare parts demand may produce the following negative situations: (i) if the demand for spare parts increases (becoming higher than the average inventory levels), and no change is made in stock deployment and supply policies, the number of stock-outs increases, leading to high backorder costs and high ordering costs, customer dissatisfaction, and inadequate maintenance activities downstream of the SC; (ii) conversely, if the demand for spare parts decreases (becoming lower than the average inventory levels), and no change is made in stock deployment and supply policies, then spare parts are not sold, resulting in high holding costs, obsolescence of spare parts, and a wrong investment of corporate economic resources; (iii) finally, if the demand for spare parts changes (decreasing or increasing), but spare parts retailers change the stock deployment and supply policies based on experience or inadequate empirical approaches, these changes may be incorrect, falling into one of the previous situations.

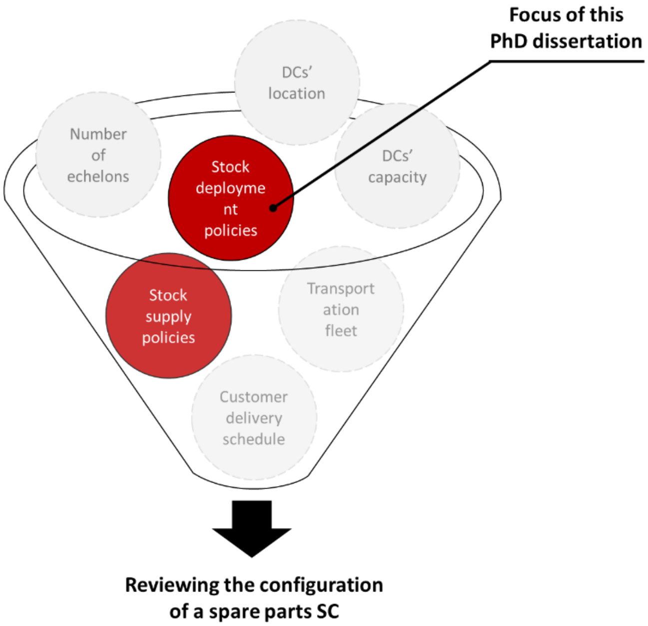

Figure 6. Main decisions that impact the review of a spare parts SC configuration and the specific focus of this thesis

To avoid these negative situations, Gregersen and Hansen (2018) strongly recommended spare parts retailers to adopt structured methodologies to review SC configuration, which implies performing two main steps. First, the optimal stock deployment policies should be outlined for each SKU, choosing how to allocate spare parts in DCs (which involves allocating customer demand to DCs and, accordingly, deciding which DC should store the inventory of each SKU). Next, the optimal supply policies should be established in each DC, choosing, for each SKU, how many stocks to supply and how often. Concerning how to review and optimise stock supply policies in a single DC, the scientific literature has provided several methodologies, such as those reported by Cohen et al. (1992), Gelders and Van Looy (1978), and Ivanov (2021). Conversely, in this project, we focus on optimising stock deployment policies for the following reason: structured methodologies to accomplish this task are overlooked by the literature, and this hampers spare parts retailers from properly reviewing their SC configurations (Abdul-Jalbar et al., 2003; Del Prete and Primo, 2021).

About the existing stock deployment policies, those possible in two-echelon spare parts SCs (Figure 4) were first mentioned in 1931 (Taylor, 1931), resulting in inventory centralisation, decentralisation, or hybrid stock deployment policies (as reported in Section 1.1). Despite the available alternatives, it is not yet clear how to associate the optimal ones with individual SKUs. Indeed, mainly qualitative discussions have been provided to compare different stock deployment policies, while quantitative comparisons have been neglected (Mangiaracina et al., 2015; Milewski, 2020). The qualitative considerations that emerged in the literature can be summarised as shown in Figure 1, translating, in terms of SC costs, into the following statements (Ding and Kaminsky, 2018). Lower facility costs arise in the case of inventory centralisation, since only one DC is managed, with few or no duplications of staff and equipment (Roundy, 1985). Moreover, given the same spare parts purchasing and production costs (which are necessary to satisfy customer demand), lower holding and ordering costs are achieved in inventory centralisation, since this stock deployment policy benefits from the risk-pooling effect, mitigating demand unpredictability (Eppen, 1979). Conversely, lower transportation costs are achieved in inventory decentralisation since multiple DCs are set, and shorter distances arise between DCs and customers (Schmitt et al., 2015). Finally, conflicting considerations can be provided regarding backorder costs, since inventory centralisation reduces the probability of inventory stock-outs owing to the risk-pooling effect, but inventory decentralisation increases SC flexibility and responsiveness, which enable higher service levels and faster deliveries in the case of emergency shipments (Zijm et al., 2019). As a trade-off, hybrid stock deployment policies can be exploited to achieve intermediate SC costs between inventory centralisation and decentralisation (Cavalieri et al., 2008).

Given the lack of quantitative methodologies to compare different stock deployment policies (and associating SKUs with the optimal one), spare parts retailers are prevented from reviewing their SC configuration, thus minimising SC total costs. To fill this gap, the scientific community has recently moved its attention towards this topic (Milewsky, 2020), identifing valuable suggestions to develop structured methodologies to optimise stock deployment policies in spare parts SCs. Specifically, many authors (Amirkolaii et al., 2017; Basto et al., 2019; Zhang et al., 2001) have recommended developing heuristic optimisation methodologies, rather than simulation or exact optimisation ones, since they provide spare parts retailers with practical solutions applicable in real companies. In fact, according to the scientific literature (Huiskonen, 2001; Sheikhar and Matai, 2022), heuristic optimisation methodologies are usually quick and easy-to-use, which fits with the needs of spare parts retailers in two ways. First, a recurrent review of the SC configuration can be performed, even in SCs with thousands of SKUs. Second, the application of such methodologies is allowed, even in spare parts retail companies, where no advanced technologies and computational resources are available (which instead are usually required to solve simulation or exact optimisation methodologies).

2.3. The impact of manufacturing options in reviewing the configuration of spare parts supply chains

The challenge of optimising stock deployment policies (thus reviewing the spare parts SC configuration) has been further complicated by the possibility of producing spare parts through two alternative manufacturing options: AM or CM. AM is the process of fabricating 3D objects directly from a computer-aided design (CAD) project, adding layers of raw material in a bottom-up process without needing tools or moulds (Ghadge et al., 2018). On the contrary, in CM, material is removed via techniques such as machining, drilling, or grinding, or being cast into moulds (Pereira et al., 2019).

Due to their opposite nature, AM and CM have different impacts on the characteristics of spare parts SCs, thus influencing the SC configuration review and the selection of optimal spare parts manufacturing technology. Specifically, as opposed to CM, AM is reported to: (i) allow greater customisation of spare parts design, thus reducing the unitary production cost of SKUs with a complex shape (Mehrpouya et al., 2022); (ii) produce fewer scraps in the manufacturing process, with evident benefits in terms of SC sustainability and raw material purchasing costs (Priarone et al., 2021); and (iii) minimise assembly costs and times, since the component functionalities are consolidated into a single piece through a near-net shape production, with appreciable effects on the unitary cost of SKUs (Holmström et al., 2010). Additionally, as a single operator can control two or more 3D printers, the number of operators required and the consequent labour cost are reduced, which is a percentage of the overall cost of SKUs (Zijm et al., 2019). Since 3D printers can be installed directly into DCs ("in-house production"), and production can be moved closer to the end-customers, the decentralisation of the spare parts manufacturing is enabled (Khajavi et al., 2014). As a result, the transportation costs of delivering spare parts from DCs to customers are reduced, lower carbon emissions are produced, and the SC is made more flexible and responsive, with positive impacts on the customer service level (Pérès and Noyes, 2006). Finally, at a theoretical level, AM allows on-demand production of spare parts, leading to reduced holding costs (no need for inventories along the SC), less risks of stock obsolescence, higher feasibility in the production of small batches, and service level benefits obtained by moving the customer order decoupling point downstream in the SC (Frandsen et al., 2020). Based on the aforementioned advantages, spare parts retailers believe that AM is a strategic opportunity to improve SC performance, which researchers have confirmed by reporting that AM is expected to gradually replace CM in the near future (Xu et al., 2021).

However, AM technology has not yet reached the level of maturity of CM, and, despite its constant evolution, it currently suffers from the following limitations: the purchase cost of 3D printers is very high, AM production times can be very long (preventing not only mass production, but also the practical implementation of an on-demand spare parts production), the reliability of AM spare parts is lower than that of CM spare parts, and many post-processing activities and quality controls are required to ensure the safety of critical spare parts (Liu et al., 2014; Zijm et al., 2019). Therefore, the limitations of AM technology and the intrinsic nature of the AM process make both researchers and practitioners aware that AM is not successful in all contexts. CM has the following advantages (Chekurov et al., 2018; Tapia-Ubeda et al., 2020): it ensures lower production times when the aim is to produce large batches, resulting in lower delivery times, lower production costs, and reduced time-to-market. CM requires no investment costs for purchasing and installing 3D printers (Chaudhuri et al., 2021) and it faces fewer risks connected to the protection of intellectual property rights because of a reduced process digitalisation (Pérès and Noyes, 2006). CM also encounters fewer limitations related to the availability of raw materials and the manufacturability of large-size components (Li et al., 2017). Moreover, globally accepted standards can be followed to ensure the quality of CM spare parts, which have not yet been developed for AM spare parts (resulting in lower-quality AM products). CM allows specific elements of a broken spare part to be remanufactured without needing to change the whole item (as in AM), which leads to lower replacement costs and higher possibilities of reusing spare parts and enabling the implementation of reverse logistics (Geng and Bidanda, 2022; Xu et al., 2021). Finally, the hourly cost of manpower that controls CM production equipment is lower, while AM requires highly trained operators to use digital technologies.

In summary, AM and CM spare parts have different impacts on spare parts SCs, leading to different fixed costs of facilities, different purchasing costs of spare parts (which are directly linked to production costs), different transportation costs, different holding and ordering costs, and different backorder costs (related to the provided service levels). As such, since the manufacturing option adopted for spare parts strongly affects SC costs, it should be taken into account when optimising stock deployment policies and consequently reviewing spare parts SC configurations (Ahmed et al., 2022; Yazdekhasti et al., 2022). As mentioned in Section 1, optimal stock deployment policies are defined by searching for a trade-off between low SC costs and high service levels. Therefore, spare parts retailers need structured methodologies to associate individual SKUs with optimal manufacturing technology, then optimise stock deployment policies, and promote the overall performance of the reviewed SC configuration.

However, the existing body of knowledge comparing AM and CM spare parts is scarce and, in its preliminary stage, shows major gaps (Delic and Eyers, 2020; Weller et al., 2015). Most of the existing research on AM spare parts is on material science and manufacturing technology areas, whereas studies concerning how AM impacts spare parts SCs and what is the optimal manufacturing technology to adopt for spare parts are limited. Therefore, potential challenges arising from integrating AM technologies within existing SCs are rarely discussed, and when they are, qualitative studies are provided (Kunovjanek et al., 2020; McDermott et al., 2021). Although few quantitative analyses have been developed, many of them propose exploratory studies and simulations whose results are strongly case-specific and concern SCs with a very simple structure (Heinen and Hoberg, 2019; Xu et al., 2021). Moreover, the available quantitative studies, such as Ashour Pour et al. (2019) and Westerweel et al. (2021), evaluate the costs of SCs with AM spare parts without comparing them to the respective CM ones. Finally, according to several authors (Knofius et al., 2021; Sgarbossa et al., 2021), whenever a comparison is made between SCs with AM and CM spare parts, only single-sourced SCs are considered, neglecting the dual-sourced ones, which produce a mix of AM and CM spare parts, adopting the optimal manufacturing technology for each SKU. Given this background, a comparative study that quantitatively evaluates the performance of SCs with AM and CM spare parts, associating individual SKUs with optimal manufacturing technology, is lacking (Basto et al., 2019; Khajavi et al., 2014).

Consequently, spare parts retailers lack a structured methodology to associate both optimal manufacturing technologies and optimal stock deployment policies with individual SKUs. As a result, the optimal review of spare parts SC cannot be determined on the one hand, and the correct introduction of AM technologies in real companies is hindered on the other, since spare parts retailers cannot evaluate whether it is worthwhile to transform existing SCs by switching from CM to AM spare parts (Weller et al., 2015).

3. Research design

This section describes the research design used in this study and discusses its validity. One of the primary aspects of assessing the validity of a research study is understanding the research methods used to conduct the investigations (Borrego et al., 2009; Queirós et al., 2017). As such, Subsection 3.1 presents the research methods adopted for use in and explains how these helped to answer each research question. Subsection 3.2 then discusses the quality of this research study, evaluating the four requirements recommended by Karlsson (2016): construct validity, internal validity, external validity, and reliability.

3.1. Research methods

Research methods should be carefully selected to understand a complex reality and the meaning of actions in a specific context, and to obtain precise and trustworthy measurements that can be used for statistical analyses (Queirós et al., 2017; Reswick, 1994). To address the pre-defined research questions, the present study adopted the following research methods. To answer RQ1, an SLNA (which combines an SLR with the analysis of bibliometric networks) was performed to understand the extant literature on the topic of spare parts deployment in SC configuration, and the choice between inventory centralisation and decentralisation. The SLNA highlighted driving research streams in the analysed topic, offering research opportunities that we used to derive the next research questions (RQ2 and RQ3). Then, to answer both RQ2 and RQ3, mathematical modelling was applied along with the development of a case study or experimental research, as depicted in Figure 7. Figure 7 summarises the research methods adopted in this study, showing their connections with the research questions, the outcomes, and the collection of appended papers. The following subsections explain each research method in detail.

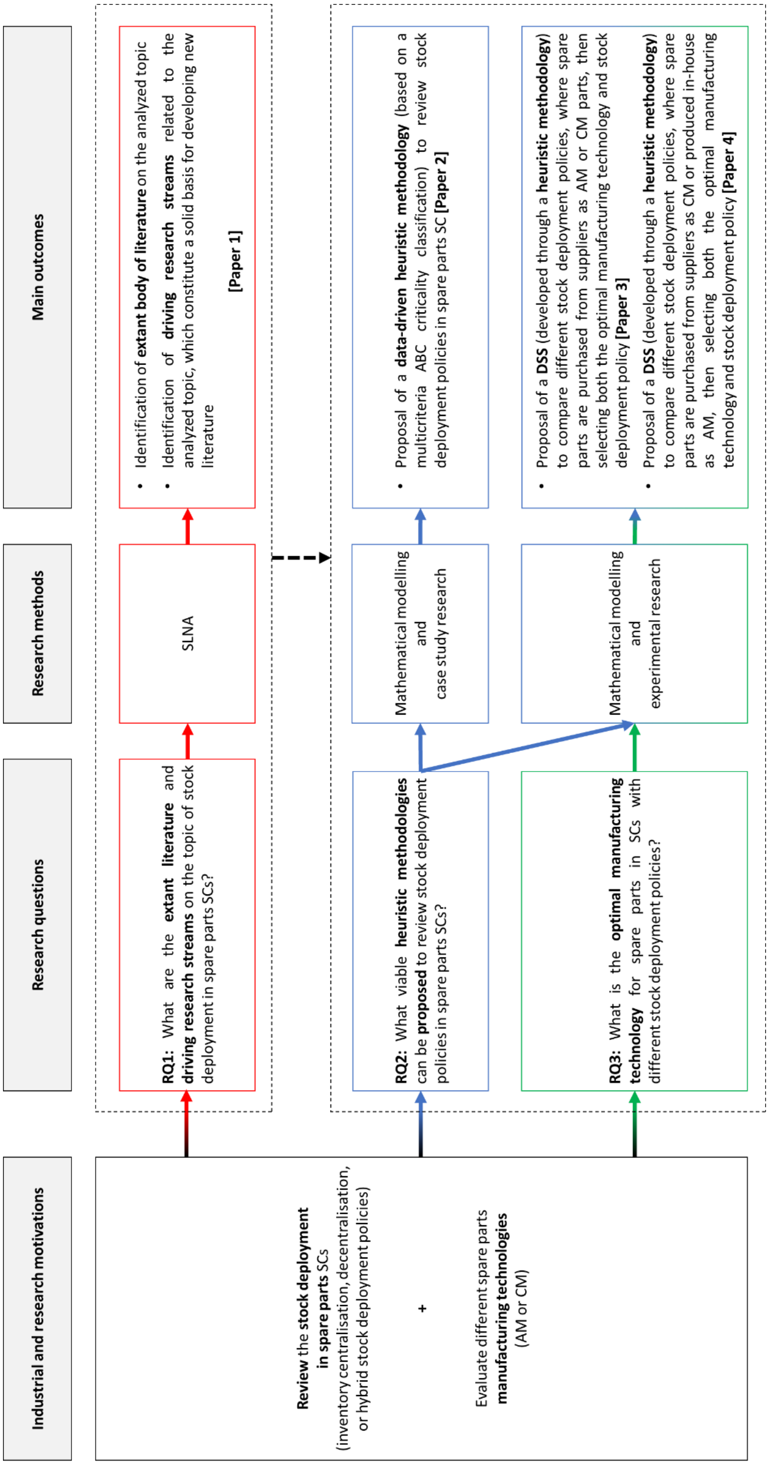

Figure 7. Research design of this project. Dashed rectangles indicate that research questions RQ2 and RQ3 were derived after answering RQ1. The colours indicate that the outcomes of papers 3-4 answered both RQ2 (blue) and RQ3 (green)

3.1.1. Systematic Literature Network Analysis

The SLNA methodology, which was introduced by Colicchia and Strozzi (2012), complements a traditional SLR by extracting and analysing quantitative information from bibliographic networks (using bibliometric tools). The SLNA was selected as the first research methodology of this study because it was specifically developed to detect the dynamic evolution of the scientific production of a discipline, highlighting research directions, emerging topics, and critical areas for the development of new knowledge (Strozzi et al., 2017). In an SLNA, the SLR represents the initial contribution, which enhances the progress of scientific research by providing a historical perspective on a selected topic and allows for an in-depth assessment of independent research activities (Mentzer and Kahn, 1995). In an SLR, which is a scientific inquiry, specific research questions are clearly formulated and reviewed using a systematic and evidence-based approach for discovering and selecting secondary data. Specifically, in an SLR, clearly defined sequential steps are applied to identify a dataset of scientific documents concerning a specific topic and pre-defined research questions (Seuring and Gold, 2012). Given its transparency, inclusivity, and explanatory and heuristic character, the SLR stands out from other research methods and is considered valid, reliable, and repeatable (Tranfield et al., 2003; Xiao and Watson, 2019). Compared with other types of literature reviews, an SLR allows for a more objective overview of the search results, eliminating bias and error issues (Buchanan and Bryman, 2009). The main purpose of an SLR is to facilitate theory development by reorganising the research carried out on a specific topic and then proposing a descriptive review of the collected works (Webster and Watson, 2002). However, according to Strozzi et al. (2017), a mere descriptive review of the works collected through an SLR, despite being appropriate to classify research contributions, is not sufficiently objective or satisfactory to identify the trends and key issues that influence the development of knowledge within a specific research field. Therefore, it is preferable to combine SLR with a subsequent bibliometric network analysis that uses objective measures and algorithms to perform quantitative literature-based detections of emerging topics. The joint use of SLR and bibliometric network analysis composes the SLNA.

In this research study, we developed an SLNA to investigate the topic of stock deployment in spare parts SCs and the choice between inventory centralisation, decentralisation, and hybrid stock deployment policies. This topic, which is the focal point of this thesis, is not well structured and investigated, and an overview of the research in this field is missing. The SLNA was used to define the extant body of knowledge in the analysed domain, identify the literature gaps and driving research streams, and lay the foundation for future research activities (which inspired the next research questions). First, following the indications of Tranfield et al. (2003), we conducted a preliminary SLR. To this end, the relevant keywords for the research study were identified and combined, generating a search query. The search query was then used to find relevant scientific contributions in the Scopus database. Next, we defined the exclusion and inclusion criteria, which were used to refine the investigation, excluding scientific contributions not pertinent to the subject areas of Engineering, Mathematics, Decision Science, and Management, and filtering out any Articles and Conference papers not written in English. Finally, based on a semantic clarification proposed by Melo et al. (2009), we manually selected the scientific contributions by consulting their title, keywords, and abstract and excluding the papers not related to the topic of interest. Indeed, as reported by Melo et al. (2009), when using keywords related to the topic of "stock deployment" and its synonyms or abbreviations, Scopus finds papers dealing with three issues, where only the latter is pertinent to this research study: (i) planning the allocation of items within a single DC, for example, placing the articles on the shelves of a warehouse or planning how many items to allocate in a single DC [19]; (ii) choosing the geographical site for building a new warehouse [20]; and (iii) determining how to allocate SKUs in multiple DCs, choosing from inventory centralisation, decentralisation, or hybrid stock deployment policies [21]. Once the SLR was performed, we achieved a database of 170 scientific contributions, which was submitted to the bibliometric network analysis by leveraging three software packages (*Microsoft Excel™, the R-tool Bibliometrix*, and *VOSviewer*). Specifically, the most productive authors, journals, and countries in the field were defined based on the number of publications. The most influential authors, journals, countries, and documents in the field were determined based on the number of citations and the Citations Per Publication (CPP) rate. Finally, we determined the main driving research streams in the field by examining the co-occurrence of authors' keywords and developing a thematic map following the procedure suggested by Cobo et al. (2011).

3.1.2. Mathematical modelling

Mathematical modelling investigates a real-world problem by describing it in mathematical concepts and language (Fowler and Fowler, 1997). In mathematical modelling, equations are typically used to simplify a complex system, thus capturing the intrinsic essence of an investigated problem, and catching the main features and roles of different parameters in the system outcomes. Mathematical modelling comprises the following five main steps (Towers et al., 2020): (i) select and define the problem to be investigated; (ii) trace the problem back to a control volume that needs to be examined and clarify the laws of science and all the key variables affecting the system; (iii) formulate the science behind the system in a concise mathematical language, encoding the problem as a set of equations and simplifying assumptions that realistically represent the truth, but streamlining it as much as possible to enable analytical calculations; (iv) compute and solve the equations by gathering the required input data, submitting it into the formulas, and obtaining the result; (v) compare the results against the input data, discuss them, and draw conclusions on the general problem and the system initially defined.

Mathematical modelling was used as a research method in this study because it is particularly appropriate for examining and predicting behaviours in complex systems, where many variables arise, and accurate but concise math-based analyses could help in understanding system occurrences (Towers et al., 2020). Therefore, mathematical modelling was used to address the problem of reviewing stock deployment policies in spare parts SCs, aiming to optimise the SC configuration based on changes in many interrelated variables (e.g., spare parts demand, spare parts manufacturing technology, logistic costs, and expected service level). In Paper 2, a heuristic data-driven methodology was developed to continuously review the configuration of SCs with CM spare parts in a quick, easy-to-use way. Furthermore, in Paper 2, a mathematical model was proposed to evaluate the economic benefits achieved through the review process. In Paper 3, a mathematical model was established to compare the cost-effectiveness of different SC configurations, where the purchase of both AM and CM spare parts was evaluated as an option to replenish DCs. The mathematical model proposed in Paper 3 constituted the basic pillar through which a DSS was then developed, tested, and validated. Finally, in Paper 4, a mathematical model was proposed (which was then leveraged to obtain another DSS) to compare the cost-effectiveness of different SC configurations, where DCs were replenished by purchasing CM spare parts from suppliers or by producing AM spare parts in-house. To compute the mathematical equations and apply the mathematical models, we used Python (version 3.7.4), developing a dedicated script for each mathematical model.

When developing mathematical models and DSSs, heuristic optimisation methodologies were preferred over exact optimisation ones for the following reason. Spare parts SCs are typically characterised by a high variety of SKUs, for which stock deployment policies and manufacturing technologies should be optimised. However, as reported by Manikas et al. (2019), the computational cost and complexity associated with optimising the SC configuration for each individual SKU through exact optimisation models are practically not feasible. Many variables and constraints are involved in the optimisation of SC configurations. Hence, the search for an exact solution to the problem could result in high computational times and NP-hard operational research problems (Amirkolaii et al., 2017). Conversely, heuristic methodologies, despite accepting approximate optimisation solutions, are more applicable in real companies since they require lower investments in computational resources and advanced technologies that many enterprises still lack (Basto et al., 2019). Therefore, heuristic methodologies are preferred to provide spare parts retailers with practical solutions for reviewing the SC configuration in real companies (Zhang et al., 2001).

3.1.3. Case study research

Case study research is an established research method recommended for investigating real-life phenomena associated with variables and complexity that are not yet sufficiently understood (Creswell, 2012). Case study research can be used to explain, describe, and explore phenomena and events in the everyday contexts in which they occur (McCutcheon and Meredith, 1993). Hence, case study research allows for a more naturalistic understanding of an issue with respect to other experimental investigations (Barratt et al., 2011). The case study findings can have implications for both theory development and theory testing. They may establish, strengthen, or weaken historical explanations of a case (Yin, 2009). Moreover, they can demonstrate the potential of a methodology by applying it in real contexts. Finally, in certain circumstances, they allow theoretical considerations to be generalised beyond the particular case studies being investigated (George and Bennett, 2005). Case study research may be approached in different ways, but it usually involves the following three steps: (i) define the case study (or case studies) to be examined; many criteria can be used to select a case study (Eisenhardt and Graebner, 2007), but the mandatory prerequisite is that it should allow researchers to access databases, staff, organisation, processes, or whatever else constitutes the analysed system; (ii) collect multiple data, information, and sources of evidence about the case study using a range of quantitative (e.g., questionnaires and database consultation) and qualitative techniques (e.g., interviews, focus groups, and observations); and (iii) analyse, interpret, and report the case study, offering a coherent interpretation of its behaviour based on the collected sources of data.

In this work, case study research was used to accomplish several tasks. First, it allowed us to formulate the problem to be investigated in this research study. As described in Section 1.2, the present research study stemmed from a specific request for support made by two companies working in the spare parts retail sector (one from southern Europe and the other from northern Europe). Focus groups with company managers and repeated inspections in companies' DCs (together with a simultaneous consultation of the scientific literature) revealed difficulty for spare parts retailers to configure SCs. In particular, the lack of structured methodologies to review and align stock deployment policies with ever-changing customer needs was highlighted as the main gap. Consulting company experts from the two available case studies also allowed us to confirm whether, in the proposed heuristic optimisation methodologies, the modelled SC configuration scenarios (with varying stock deployment policies and manufacturing technologies) and the assumed simplifying assumptions were sufficiently realistic. These scenarios and hypotheses were derived by consulting the scientific literature. However, they were validated or appropriately integrated after subjecting them to verification by company experts. Finally, the case study research allowed us to answer RQ2. The two available case studies were used to test and validate the data-driven methodology proposed in Paper 2 on two real companies. From this perspective, the advantages of the proposed data-driven methodology were highlighted by comparing the performance associated with the starting SC configuration (extracted from the available databases) and the performance obtained after reviewing the stock deployment policies. In addition, consulting with company experts made it possible to verify the results of the mathematical modelling, ensuring their reliability not only from the viewpoint of our research team but also for experts with decades of experience in the field of spare parts retail. Finally, the availability of two different case studies offered the opportunity to directly compare multiple cases and replications, remarking their similarities and differences (Bazeley, 2020; Dinwoodie and Xu, 2008). In line with the claims of several authors (Voss et al., 2002; Yin, 2009), considering two different case studies enabled us to generalise the findings and devise new theoretical considerations on the relationships between different causes and effects.

3.1.4. Experimental research

Experimental research (also known as hypothesis testing or deductive research method) rigidly follows a scientific research design to test or prove a hypothesis by way of experimentation, and uses advanced analytic techniques (such as machine learning, text mining, predictive modelling, data mining, and statistical analysis) to capture, manage, and process cause-and-effect links between many factors (Pollfish, 2022). Therefore, during experiments, researchers gather evidence that may be used to support or deny the pre-defined hypothesis. Moreover, new insights are gained on a particular problem, and then better and faster decisions are made to fix it (Voxco, 2022).

In this study, experimental research was selected as the research method because, among its possible uses, it has been demonstrated to be a valid strategy for gaining insights into SC efficiencies and driving SC optimisation (Paksoy et al., 2016). Specifically, experimental research was applied to answer RQ2 and RQ3, developing the two DSSs proposed in Papers 3 and 4, respectively. The procedural steps followed in this project to implement experimental research are reported in this section. Before describing these steps, it is worth noting that they may seem similar to the procedural steps suggested for big data analytics (Chen et al., 2016; Tsai et al., 2015). However, in this case, it is more appropriate to refer to is as experimental research rather than as big data analytics due to the definition of big data. In fact, big data are defined as very large and diverse (structured, semi-structured, or unstructured) datasets, coming from different sources (e.g., sensors, video/audio, log files, transactional applications, web, and social media), whose size or type is beyond the data mining ability of traditional analytic techniques (Shi, 2022; Tsai et al., 2015). However, despite managing “many data” in this research project, we did not handle “big data” since they all came from the same source, and were all characterised by a similar structure.

Concerning the experimental research procedural steps, first, a set of input data was prepared as follows. After defining the problem to investigate, appropriate mathematical models (with their respective assumptions and independent input parameters) were defined, as described in Section 3.1.2. Then, where appropriate, an analysis of variance (ANOVA, with Main Effect Plot) was developed to exclude from the analysis the independent input parameters whose variation had a negligible impact on the results of the mathematical models. In this way, the number of input parameters was reduced, facilitating the subsequent training of machine learning algorithms and reducing the time and computational costs of this task. At this point, the Sobol quasi-random low discrepancy sequence (S_{mn}) was used to associate each remaining independent parameter (not excluded in the ANOVA) with quasi-random realistic values, combining them to derive thousands of different SC configuration scenarios (i.e., SCs characterised by different stock deployment polices, spare parts manufacturing technologies, spare parts demand, logistic costs, and service levels). Specifically, the value of each independent input parameter (par) was varied according to Equation 1, where N is the total number of SC configuration scenarios to be created, n is the specific scenario considered, M is the total number of input parameters, m is the specific input parameter to which we assign a Sobol value (par_{mn}), and par_{ll} and par_{ul} are the lower and upper limits admitted for the value of the considered input parameter.

$$par_{mn} = par_{ll} + S_{mn} \cdot (par_{ul} - par_{ll}) \; with \; m = 1, \dots, M \; and \; n = 1, \dots, N \qquad (1)$$

The Sobol quasi-random low discrepancy sequence was used as a sampling strategy because, when studying problems with numerous input parameters, it has been reported to better (more uniformly) cover the space of combinations of the admissible input parameter values with respect to other strategies (i.e., discrete sampling or Monte Carlo) (Bicchi et al., 2022; Burhenne et al., 2011). Therefore, once the Sobol input data were defined, each SC configuration scenario was submitted to the mathematical models, achieving a parametric analysis by replicating the models' application. Finally, the results of the parametric analyses were used to feed and train decision tree algorithms, thus exploiting the capability of machine learning to understand and interpret correlations among the many parameters affecting a system (Arena et al., 2021). As an outcome, DSSs were obtained in the form of decision trees, which allowed us to extrapolate from the results of the parametric analyses general considerations on how to review the configuration of spare parts SCs, choosing both the optimal stock deployment policies and the manufacturing option. To provide spare parts retailers with quick and user-friendly DSSs, decision tree algorithms were selected for the experimental research, which are known for being intuitive and effective decision-making tools among machine learning algorithms (Sgarbossa et al., 2021). The Gini-diversity index was used to split the branches of the decision trees, following the indications by Arena et al. (2021). Moreover, to validate the performance of the decision trees and avoid under- or overfitting issues, a five-fold cross-validation process was carried out together with the pruning of the tree, as suggested by Bradford et al. (1998) and Morgan et al. (2003). Finally, the following key performance indicators (KPIs) were calculated to evaluate the general performance of each DSS and the performance of each leaf:

- total accuracy of the decision tree (A, Equation 2), given by the ratio between the number of correct predictions ($\#correct\ predictions_{tree}$) and the number of total predictions in the tree ($\#predictions_{tree}$, initial dataset size);

$$A = \frac{\#correct\ predictions_{tree}}{\#predictions_{tree}} \tag{2}$$

- the accuracy of each leaf (a, Equation 3), calculated as the ratio between the number of correct forecasts ($\#correct\ forecasts_{leaf}$) and the number of total forecast in the considered leaf ($\#forecasts_{leaf}$);

$$a = \frac{\#correct\ forecasts_{leaf}}{\#forecasts_{leaf}} \tag{3}$$

- the number of elements in each leaf (p, Equation 4), calculated as the ratio between the number of elements classified within the considered leaf ($\#forecasts_{leaf}$) and the number of total elements to be classified ($\#forecasts_{leaf}$, that is the size of the starting dataset);

$$p = \frac{\#forecasts_{leaf}}{\#forecasts_{tree}} \tag{4}$$

- the expected percentage of cost increase (c, Equation 5) to be paid by the spare parts retailer in case an element is wrongly classified in a leaf (wrong tree forecast), calculated as the average of cost increases associated with wrong forecasts.

$$c = \frac{\sum_{h=1}^{\#wrong\ forecasts_{leaf}} \left(\left| \frac{cost\ of\ wrong\ forecast - cost\ of\ correct\ forecast_h}{cost\ of\ correct\ forecast_h} \right| * 100 \right)}{\#wrong\ forecasts_{leaf}} \tag{5}$$

Regarding the tools and software used for experimental research, Python (version 3.7.4) was used as a programming environment, exploiting the open-source library “Scikit-learn” for machine learning purposes. Moreover, as a computational resource, the “Idun” cluster provided by NTNU was used to run calculations, where Idun is a high-performance computing group. Finally, Minitab software and Microsoft Excel were used to perform some statistical analyses (such as ANOVA).

3.2. Research quality

To judge the research quality of this study, according to Karlsson (2016), four requirements were verified (i.e., construct validity, internal validity, external validity, and reliability), which are considered suitable for evaluating both quantitative and qualitative investigations (Halldórsson and Aastrup, 2003; Voss et al., 2002). For each requirement, a specific subsection is provided below to explain how this was satisfied during the research process, leading to good-quality results, which can be considered reliable and ethical by other researchers and practitioners.

3.3.1. Construct validity

Construct validity assesses the extent to which correct operational definitions have been established for the concept under analysis (Voss et al., 2002). To account for construct validity, Yin (2009) proposed two fundamental aspects: (i) offer clear definitions of what is to be investigated, and (ii) demonstrate that the operational definitions truly represent what is intended to be investigated.

In this thesis, Section 1 provides a clear description of the research scope. Definitions and explanations of the investigated topics are also presented in both the main report (Part I) and all the appended papers (Part II). Furthermore, in line with Yin (2009), efforts were made to maintain a clear chain of evidence, meaning that, starting from the input data and information collected, readers should be able to trace the derivation of all the findings. To achieve a clear chain of evidence, to the extent possible, the reasons for each research activity, the decisions made to conduct the investigations, and the results obtained were documented and reported in this study. Regarding the mathematical modelling, the case study research, and the experimental research, verification, and validation techniques were used to ensure that the research reflected what was intended.

3.3.2. Internal validity

Internal validity implies revealing the correct causal relationships among variables and avoiding ignoring factors that, instead, concur in explaining these correlations (Karlsson, 2016). In other words, if it is concluded that X has been caused by Y, overlooking the fact that X has also occurred as a result of Z, the internal validity is low. Internal validity is more appropriate as an evaluation criterion, particularly in exploratory and causal research, but not necessarily in descriptive studies (Croom, 2008; Yin, 2009).

If the question of internal validity does not arise in descriptive and exploratory research, one of the key techniques used to ensure internal validity is theoretical replication. This strategy was used in this study, for example, when developing mathematical models and applying them to example case studies comparing different scenarios of SC configuration (with different degrees of inventory centralisation). The results expected in each SC configuration scenario were formulated based on the scientific literature (before data collection). Then, once the case study research was performed, the findings were compared with the predictions, confirming the homogeneity between the expected and achieved results. Regarding mathematical modelling and experimental research, the system's behaviour and the identification of causality were the main curiosities that drove the entire research.

In this case, causality was established by adjusting each independent variable individually and then evaluating the causal effects on the dependent variables (Bertrand and Fransoo, 2016; Croom, 2008).

3.3.3. External validity

External validity refers to the extent to which the findings of a research study can be generalised from specific data and contexts to broader ones (Cook et al., 1979; Seale, 1999). To ensure the external validity of a research study, specific descriptions of the data and context in which the study was carried out should be provided. Such detailed descriptions allow readers to judge whether the research findings are transferable to other situations. From this perspective, the present research study aimed to describe the specific SC configurations investigated and report in the appended papers the simplifying hypotheses assumed to develop the methodologies and DSSs. Moreover, concerning the case studies used to perform the investigations, detailed information on the companies analysed and their characteristics was offered. Furthermore, to ensure the greatest generalisability of this research study, multiple scenarios of SC configurations were studied, strongly varying their degrees of centralisation and the characteristics of spare parts (demand, procurement lead time, service level, etc.), thus referring to as many realistic situations as possible.

3.3.4. Reliability

Reliability refers to the extent to which the research may be repeated and provide the same results (Voss et al., 2002). Therefore, in a reliable research study, bias is minimised so that the same findings can be achieved by other researchers who replicate the study. To ensure reliability, two main strategies were adopted. First, we provide a detailed description of the research design and the methodologies used to develop the study (Section 3). This information is also reported in the appended papers, further enabling other researchers to repeat the investigations. Second, to prevent a single researcher from perpetrating any bias, several researchers were involved analysing the data and the achieved results.

4. Research results

This section presents and discusses the results and findings of this research project. Following the research design (Figure 7), we began the study by performing an SLNA that addressed **RQ1** (What are the extant literature and driving research streams on the topic of stock deployment in spare parts SCs?). Two outcomes were obtained: (i) identification of the extant body of literature on the topic of stock deployment in spare parts SCs; and (ii) identification of the driving research streams, which mainly concur in developing the literature in this field. Both outcomes of RQ1 are presented in Subsection 4.1, based on **Paper 1**. From these outcomes, we derived two additional research questions (**RQ2** and **RQ3**), which prompted the next advancement of this project.

Aiming to answer **RQ2** (What viable heuristic methodologies can be proposed to review stock deployment policies in spare parts SCs?), we exploited different approaches, proposing as outcomes three different heuristic methodologies for optimising stock deployment policies in spare parts SCs. The first is a data-driven heuristic methodology, which was developed using mathematical modelling and case study research. This is presented in Subsection 4.2, and is based on **Paper 2.** The second and third heuristic methodologies, which allowed the development of two DSSs, were conceived **to answer not only RQ2 but also RQ3** (What is the optimal manufacturing technology for spare parts in SCs with different stock deployment policies?). By exploiting mathematical modelling and experimental research, two complementary heuristic methodologies (and two consequent DSSs) were developed, which allowed us to review the configuration of spare parts SCs in the following situations:

1. SCs where spare parts are purchased from suppliers as AM or CM finished products, and the aim is to select, for each SKU, the combination of the stock deployment policy and manufacturing option (purchase of CM or AM spare parts) that minimises the SC total cost.
2. SCs where stocks of spare parts can be purchased from suppliers as CM finished products or produced in-house as AM products (by installing 3D printers in each DC), selecting, for each SKU, the combination of stock deployment policy and manufacturing option (purchase of CM spare parts or production of the AM ones) that minimises the SC total cost.

The outcomes of both RQ2 and RQ3 are presented in Subsection 4.3, where Subsection 4.3.1 describes the first DSS (based on **Paper 3**), and Subsection 4.3.2 describes the second one (based on **Paper 4**).

4.1. Extant literature on stock deployment in spare parts SCs and driving research streams

When presenting the theoretical background (Section 2), we explained the importance of optimally configuring spare parts SCs and reviewing the configuration of existing SCs during the business' lifetime. In this context, we pointed out that structured methodologies for reviewing the configuration of spare parts SCs should help spare parts retailers optimise two fundamental aspects. First, optimal stock deployment policies should be outlined for each SKU, opting for inventory centralisation, decentralisation, or hybrid stock deployment policies. Next, the optimal supply policies should be established in each DC, choosing for each SKU how many stocks to supply and how often. However, as confirmed by many authors (Gregersen and Hansen, 2018; Huiskonen, 2001; Tapia-Ubeda et al., 2020), we found that, while numerous methodologies have already been provided by the literature to optimise stock supply policies in a single DC, few have been provided to optimise stock deployment policies in multiple DCs. Therefore, we found that this literature gap hampers the optimal review of SC configurations and thus reduces the potential for success of spare parts retailers. To fill this gap, we defined the first research question (RQ1), which was then answered by developing an SLNA. The SLNA achieved the following two outcomes. As the first outcome, the extant body of literature on the topic of stock deployment in spare parts SCs was defined. This outcome allowed us to provide spare parts retailers (and researchers) with an overview of the body of knowledge on the investigated topic. We then reorganised the research carried out so far by identifying the main contributions, as well as the most prolific authors, journals, and countries (based on the number of publications), and the most influential ones (based on the number of citations). Subsequently, based on the identified body of literature (first outcome), we derived the second outcome, which was represented by identifying the driving research streams that mainly concur in developing the literature on the topic of stock deployment in spare parts SCs. The driving research streams were considered a solid basis on which to build new research studies, attracting the attention of both researchers and practitioners. Hence, by combining the identified driving research streams with the specific support requests received by companies (mentioned in Section 1.2), we selected two of them (restricting the design space for time reasons) to focus our attention on and derive the next research questions. The following subsections summarise each outcome of the SLNA.

4.1.1. Extant literature on stock deployment in spare parts SCs

By performing an SLNA, the existing literature on stock deployment in spare parts SCs was traced back to 170 documents (66% Articles and 34% Conference Papers) published by 413 authors in 109 journals over 91 years (1931-2022). These 170 documents represent the first outcome of the SLNA. Their temporal evolution of publications (blue) and citations (orange) was mapped (Figure 8), highlighting 1931 as the year in which the importance of stock deployment policies in spare parts SCs was first mentioned (Taylor, 1931). Although it has been almost 100 years since the importance of stock deployment was first remarked upon, the SLNA demonstrated (Figure 8) that the literature in this field is lacking (especially until 2008), confirming the motivation behind this research project, and revealing a recent interest of the scientific community towards this topic.

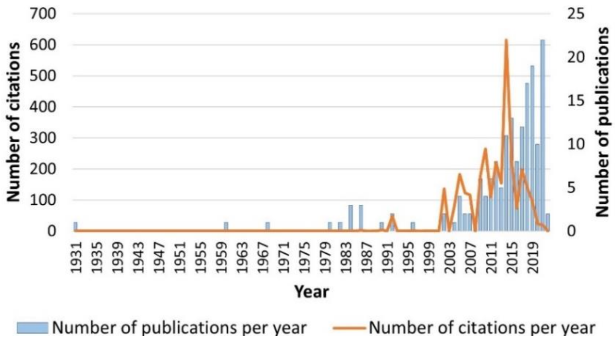

Figure 8. Reference publication (blue) and citation (orange) year spectroscopy

The geographical distribution of publications and citations (Figure 9) outlined the most productive and influential countries on the topic of stock deployment in spare parts SCs, where productivity was assessed based on the number of publications, and influence was assessed based on the number of citations. China, Germany, the Netherlands, and Italy appeared to be the most productive countries (138, 45, 43, and 43 publications, respectively), while Finland, the United States, and the Netherlands emerged as the most influential ones (779, 473, and 397 citations, respectively). The only country leader in both fields was the Netherlands, revealing the importance of not limiting the literature analysis to the most productive countries in the field but also extending the investigation to other less prolific ones. This consideration was also applied to authors and journals, explaining why this study analysed both the productivity and influence of countries/authors/journals.

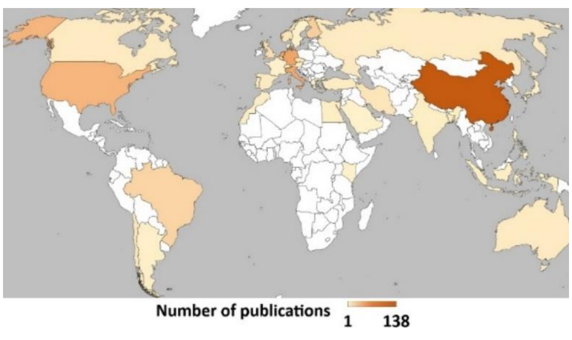

Figure 9. Total number of publications per country

Concerning the journals, the most productive and influential were defined by performing three analyses. First, the journals mostly devoted to the considered topic were determined by applying Bradford's Law (Bradford, 1934), resulting in the 11 core sources listed in Figure 10. Second, the publication trend of the top 5 core sources (Figure 11) was used to show the journals' persistence over time, where only the European Journal of Operational Research (EJOR) presented regular publications on the topic of stock deployment in spare parts SCs in the last 15 *years. Third, the most influential journals in the field were defined by calculating their average number of CPP (Equation 6), highlighting Computers in Industry as the most influential journal, with the highest CPP (*

Table 1).

$$CPP = \frac{Total\ number\ of\ citations}{Total\ number\ of\ publications} \tag{6}$$

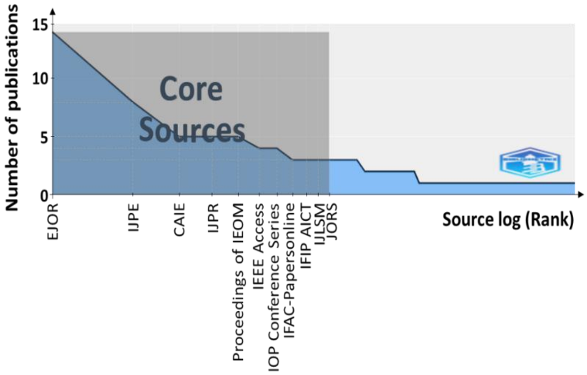

Figure 10. Most productive journals (core sources), according to Bradford's law

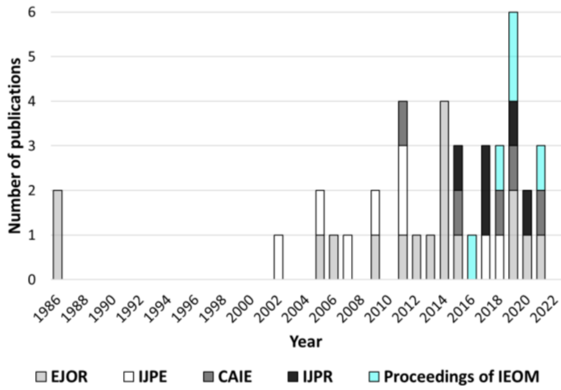

Figure 11. Publication trend of the top 5 core sources

Table 1. Top 5 most influential journals based on CPP

Source (with references)	Number of publications	Number of citations	CPP
Comput. Ind. (Khajavi et al., 2014)	1	400	400
J. Manuf. Technol. Manag. (Holmström et al., 2010; Meisel et al., 2016)	2	276	138
Rel. Eng. Syst. Saf. (Costantino et al., 2013)	1	86	86
Prod. Plan. Contr. (Abdallah et al., 2012; Chandima Ratnayake, 2019; Liu et al., 2014)	3	255	85
IIE Transactions (Caglar et al., 2004)	1	81	81

Lastly, we reorganised the main information on authors' productivity and influence in a graphical descriptive tool (Figure 12), which summarised the following notions: the most influential authors in descending order of CPP (y-axis), their temporal publication cadence (dot distribution), the annual number of publications (dot size), and the annual number of citations (dot colour). Figure 12 not only shows the most productive (Van Houtum) and most influential authors (Partanen, Khajavi, and Holmström) in the field, but it also emphasises the two most influential documents in the literature on stock deployment in spare parts SCs. These two documents are shown by the red and yellow dots in the upper part of Figure 12 (papers with the highest CPP). By consulting these documents (Holmström et al., 2010; Khajavi et al., 2014) an important consideration emerged: the two most influential publications in the field of stock deployment in spare parts SCs deal with the same research stream. This research stream which, as a matter of fact, is attracting the attention of the scientific community, investigates how to optimise stock deployment policies in SCs with AM spare parts (where AM is an opportunity to revolutionise the configuration of spare parts SCs).

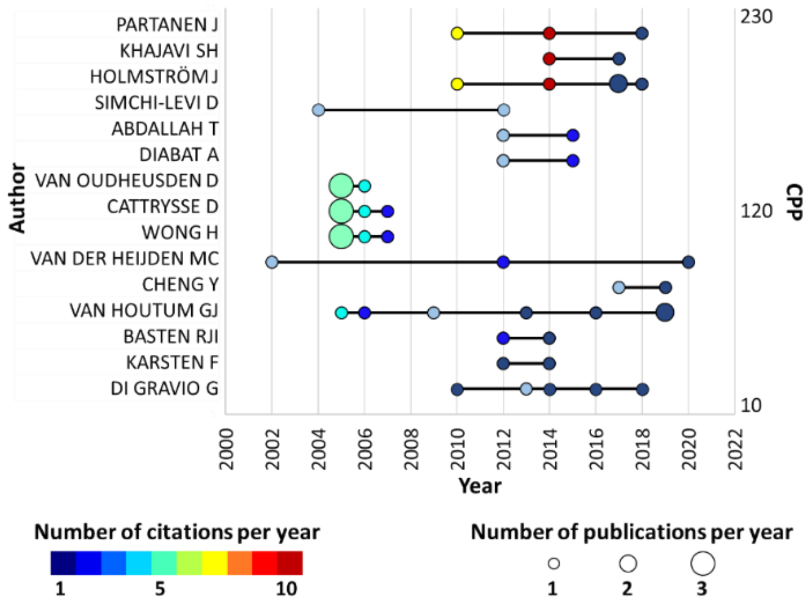

Figure 12. Qualitative Authors' Relevance Assessment

4.1.2. Driving research streams on stock deployment in spare parts SCs

After defining the extant literature on stock deployment in spare parts SCs, to answer RQ1, two additional analyses were performed to denote the driving research streams related to the topic under investigation. These additional analyses took as input information the first outcome of the SLNA (namely, the 170 documents representing the extant literature on the topic of stock deployment in spare parts SCs). In the first additional analysis, we explored the authors' keywords reported in each document and their co-occurrence. Figure 13 depicts the achieved results, showing the links between keywords with a minimum number of co-occurrences of two. Based on the colours in Figure 13, five main research themes related to the topic of stock deployment in spare parts SCs were identified, which were confirmed by consulting the abstracts of the 170 papers: (pink) the optimal deployment of spare parts in SCs with single or multi-location DCs and two or multiple echelons; (red) the optimisation of stock deployment in SCs with AM spare parts, where AM is considered an opportunity to switch from centralised to decentralised SCs, revolutionising the stock deployment policies of spare parts; (yellow) the optimisation of spare parts deployment to improve maintenance activities in the specific sectors of aeronautics and military industry; (brown) the optimisation of stock deployment in spare parts SCs where emergency and lateral shipments are allowed; (green) sustainability and reverse logistics with a focus on optimising stock deployment in closed loop spare parts SCs. These five main themes can be used to divide the extant literature in the field into appropriate clusters.

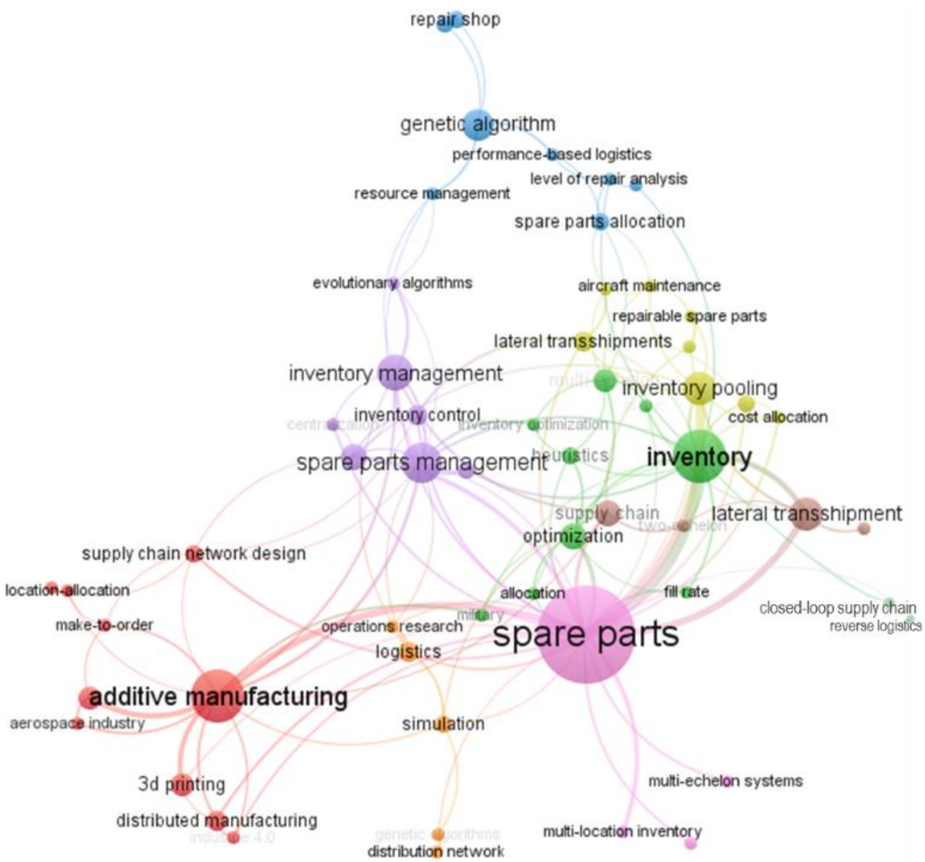

Figure 13. Co-occurrence of authors' keywords mapped through VOSviewer

Finally, as the second additional analysis, we built a Thematic Map of the authors' keywords, following the indications by Cobo et al. (2011). Figure 14 presents the achieved Thematic Map. Based on the five research themes that emerged in Figure 13, Figure 14 emphasises two of them as driving (motor) research streams that mainly concur in developing the literature on the analysed topic:

1. the optimisation of stock deployment in closed loop spare parts SCs;
2. the optimisation of stock deployment in SCs with AM spare parts.

Moreover, Figure 14 highlights a third driving research stream, which refers to the specific methodology used for planning stock deployment:

3. the use of heuristic optimisation (instead of exact optimisation or simulation) to review the stock deployment policies in spare parts SCs.

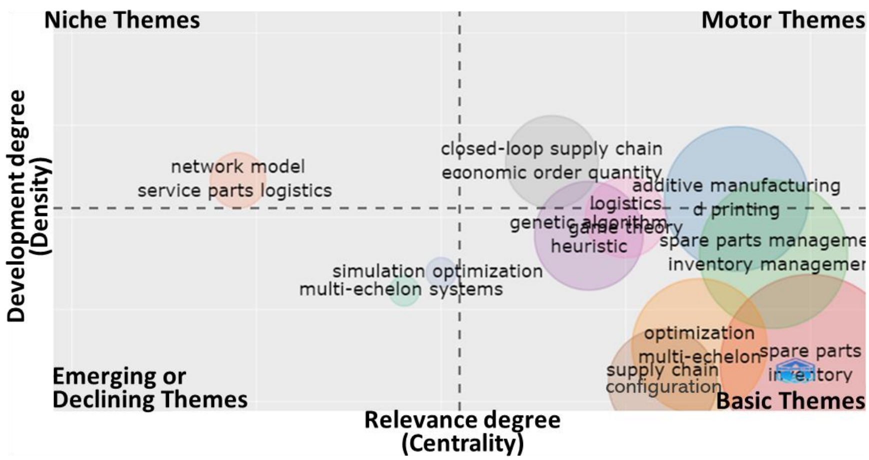

Figure 14. Thematic Map of the authors' keywords built through Bibliometrix (R-tool)

The three driving research streams listed above represent the second outcome of RQ1. Such research streams can hopefully inspire future research challenges, favouring the development of the literature on stock deployment in spare parts SCs. Accordingly, these streams were used in the present research project to formulate new research opportunities. However, investigating all three driving research streams (with all the research questions attributable to them) would have exceeded the research time frame. Hence, we decided to focus only on the last two driving research streams, deriving, for each of them, a new research question (as depicted in Figure 7 and summarised in Table 2). The derivation of these new research questions (RQ2 and RQ3) is not accidental, but it is justified in Section 1.2, explaining both the industrial and theoretical motivations behind this research project. Notably, RQ2 and RQ3 are not the only possible research questions that can fulfil the research opportunities related to the selected driving research streams. This is not to diminish the importance of the present project but rather to emphasise how many more research possibilities can be created through the outcomes of RQ1.

Table 2. Additional research questions derived from two of the identified driving research streams

Selected driving research stream	Derived research question
The use of heuristic optimisation to optimise the stock deployment in spare parts SCs	**RQ2:** What viable heuristic methodologies can be proposed to review stock deployment policies in spare parts SCs?
The optimisation of stock deployment in SCs with AM spare parts	**RQ3:** What is the optimal manufacturing technology for spare parts in SCs with different stock deployment policies?

Aiming to answer RQ2 and RQ3, three outcomes were achieved, where, as depicted in Figure 7, one of them (novel data-driven heuristic methodology) answers only RQ2, while the remaining two (two DSSs) answer both RQ2 and RQ3. For this reason, the results and findings of RQ and RQ3 are presented in the following sections. Section 4.2 presents the outcome, which answers only RQ2. Section 4.3 describes the two outcomes, which answer both RQ2 and RQ3.

4.2. Data-driven heuristic methodology to review stock deployment policies in spare parts SCs

Despite the importance of regularly reviewing stock deployment policies (and the consequent SC configuration) in existing spare parts SCs, the literature lacks methodologies to accomplish this task (Eldem et al., 2022; Van der Auweraer and Boute, 2019). For this reason, nowadays, many spare parts retailers never review their starting SC configuration, and often the stock deployment policies are chosen only once (based on experience and arbitrary evaluations) and are never questioned (Hu et al., 2018). To fill this gap, multiple authors (Sheikhar and Matai, 2022; Teunter et al., 2010) have suggested a valuable method, which was confirmed by the outcomes of RQ1 in this study, namely, providing spare parts retailers with heuristic methodologies for reviewing stock deployment policies in existing spare parts SCs. Heuristic optimisation methodologies are usually quick and easy-to-use (Manikas et al., 2019). Moreover, they are more applicable in real contexts (in respect to exact optimisation or simulation methodologies) since they require fewer computational resources and less advanced technologies, which are still lacking in many companies (Basto et al., 2019; Zhang et al., 2001). Based on this research opportunity, **RQ2** was formulated. Then, aiming to answer RQ2, we followed two different approaches, which led to multiple outcomes (as indicated in blue in Figure 7). The present subsection refers to the first outcome of RQ2, which is a novel data-driven heuristic methodology proposed to support spare parts retailers in reviewing the configuration of existing spare parts SCs. The remaining outcomes of RQ2 are described in Subsection 4.3 since they answer both RQ2 and RQ3 at the same time.

As the first outcome of RQ2, a novel data-driven heuristic methodology (called "SP-LACE –Spare Parts suppLy chAin Configuration rEview") was developed and proposed to review the configuration of existing spare parts SCs based on a multicriteria ABC criticality classification of spare parts. SP-LACE refers to the parameters reported in Table 3, which was developed by applying mathematical modelling and relying on the following simplifying assumptions: (i) DCs have an unlimited capacity (Tapia-Ubeda et al., 2020); (ii) no costs related to the purchase or rental of DCs are considered since existing SCs are evaluated where the spare parts retailer already owns DCs (Cantini et al., 2022); (iii) inbound and outbound transportation costs are considered negligible compared with other SC costs (Cohen et al., 1988); (iv) no issues related to spare parts sustainability and closed loop SCs are considered (Zijm et al., 2019); and (v) procurement lead times are assumed deterministic (Lolli et al., 2022), while spare parts demand is assumed stochastic (Liu et al., 2014). Specifically, a normal distribution is assumed for SKUs with an average demand during the procurement lead time greater than 15 units, while a Poisson distribution is taken for the other SKUs (Italian Technical Commission for Maintenance, 2017; Syntetos and Boylan, 2006); (vi) a continuous (ROP, Q) inventory policy is used to manage stocks in DCs, where ROP is the reorder point and Q is the optimal order quantity (Fathi et al., 2021; Sapna Isotupa, 2006).

Table 3. Summary of SP-LACE parameters

Parameter	Description	Unit measure
r	Considered SC configuration. r is 0 in the starting SC configuration, while being 1 in the reviewed SC configuration	-
i	Considered DC. i assumes integer values between 1 and the total number of DCs ($\#DCs$)	-
k	Considered SKU. k assumes integer values between 1 and the total number of SKUs ($\#SKUs$)	-
$Period\ of\ analysis$	Time interval considered to evaluate the cost performance of the SC	time
uc_k	Unitary cost of purchasing each SKU from the supplier	€/unit
$h_{\%}$	Holding cost rate for keeping inventory of SKUs in the period of analysis. According to Khajavi et al. (2014), it includes the obsolescence rate of SKUs	$time^{-1}$
$X_{i,k,r}$	Total demand received for each SKU in each DC in the period of analysis. It depends on the demand distribution $x_{i,k,r}$, which can be a normal or a Poisson one, as already explained	units/time
$\overline{x_{i,k,r}} * LT_{i,k}$	Average demand received for each SKU in each DC during the procurement lead time	units

$\sigma(x_{i,k,r})$	Standard deviation of the demand for each SKU in each DC during the period of analysis. It is considered when the demand distribution ($x_{i,k,r}$) is normal	units/time
$LT_{i,k}$	Procurement lead time of each SKU in each DC	time
$\#Ord_{i,k,r}$	Number of supply orders issued by the analysed company in the period of analysis to replenish each SKU in each DC	supply orders/time
$QOrd_{i,k,r}$	Total quantity of each SKU ordered by the analysed company to replenish each DC in the period of analysis	units/time
oc_k	Cost of issuing one supply order for a SKU	€/supply order
$uback_k$	Unitary backorder cost of each SKU	€/backorder
$SL_{i,k,r}$	Desired service level for each SKU in each DC	-
$Q'_{i,k,r}$	Optimal order quantity of each SKU in each DC	units
$ROP'_{i,k,r}$	Reorder level associated with each SKU in each DC	units
$SS_{i,k,r}$	Safety stocks calculated to compensate demand fluctuations of each SKU in each DC according with the desired service level	units
$Z_{i,k,r}$	Service factor associated with the desired service level ($SL_{i,k,r}$) in a standardised normal distribution	-
$cost\ limit_k$	Threshold value established based on the type of spare parts retailed by the analysed company	€
tc	Average time required to run the stage 1 of SP-LACE and update its mathematical calculations	time
$\#\gamma\ SKU_{depl_{i,r}}$	Number of γ SKUs in each DC, whose deployment policy changes when moving from the starting SC configuration to the reviewed one	-
$\#trips_r$	Number of displacements to be performed in the reviewed SC configuration to move stocks from decentralised DCs to the central one	-
$\#SKU_{supply_{i,r}}$	Number of SKUs in each DC, whose supply policy changes when moving from the starting SC configuration to the reviewed one	-
mh	Cost of manpower who applies SP-LACE, updating its mathematical calculations and the consequent stock deployment and supply policies	€/time
$dist$	Average distance between the central DC and the decentralised ones in the analysed company	km
Cap	Capacity of the vehicle used by the analysed company to displace SKUs between DCs and deliver them to customers	m^3
vol_k	Volume of each SKU	m^3
$utrip$	Cost per kilometer of the vehicle used to displace SKUs	€/km
tm	Average time required to update the supply policy of one SKU in the company Information Technology (IT) system	time

SP-LACE is composed of two stages, which were achieved by applying mathematical modelling as the research method. In **stage 1**, a data-driven analysis based on a multi-criteria ABC criticality classification of spare parts was performed. Hence, the results were used to review the configuration of spare parts SCs by optimising both the stock deployment policies in multiple DCs (which is the main focus of this thesis, opting for inventory centralisation, decentralisation, or hybrid stock deployment policies) and the supply policies associated with each SKU in each DC (indicating how many spare parts to supply and how often). Here, we searched for a trade-off between holding, ordering, and backorder costs in DCs. Then, in **stage 2**, for the first time in the literature, we evaluated the economic benefits of the reviewed SC configuration, seeking to show the achieved benefits and the importance of reviewing the SC configuration. To this end, a comparison is provided between the SC total cost (Table 4) before (i.e., starting SC condition) and after the review process.

Table 4. Cost items considered in SP-LACE

Costs	Description	Unit measure
C_{tot_r}	Total cost of the SC	€/time
C_{H_r}	Holding cost	€/time
C_{O_r}	Ordering cost	€/time
C_{B_r}	Backorder cost	€/time
C_{rev_r}	Cost incurred to review the SC configuration	€/time
C_{Sof}	Software cost incurred, each time the SC configuration is reviewed, to run the mathematical calculations and apply the stage 1 of SP-LACE	€/time
C_{Disp_r}	Displacement cost to transport, in the central DC, the γ SKUs that in the starting SC configuration were decentralized and, after the SC configuration review, have to be centralised (changing their deployment policy)	€/time
C_{Adm_r}	Administrative cost to update, in the IT system, the $ROP_{i,k,r}$ and $EOQ_{i,k,r}$ values of the SKUs whose supply policy has changed when moving from the starting SC configuration to the reviewed one	€/time

Stage 1 of SP-LACE comprises the following steps, which are schematised in Figure 15 (referring, as an example, to a company with 3 DCs – DC_1, DC_2, DC_3 – where DC_2 is assumed to be the central one).

In Step 0, the initial SC configuration of the company and the available DCs are identified.

In Step 1, a multi-criteria criticality classification of spare parts is accomplished in each peripheral DC (DC_1 and DC_3 in Figure 15). First, the SKUs are divided into criticality classes according to their unitary cost (HML analysis), and the historical number of supply orders issued in the period of analysis (XYZ analysis). Here, the tangent method suggested by the scientific literature (Ultsch and Lötsch, 2015; Van Wingerden et al., 2016) is applied to define the boundaries between adjacent criticality classes.

Then, the results of the two criticality classifications (HML and XYZ analyses) are merged into a single ranking, associating each SKU with the α, β, and γ criticality classes (in accordance with Figure 15).

In Step 2, the stock deployment policies are defined, indicating the need to centralise non-critical γ SKUs, while keeping the α and β ones decentralised.

In Step 3, the demand for γ SKUs is cumulated with the demand already faced by the central DC (DC_2), the multicriteria criticality classification of spare parts is carried out, and SKUs in such a DC are associated with the α, β, or γ criticality class.

Finally, in Step 4, the stock supply policies are defined for each DC. Specifically, no stock is kept for γ SKUs in DC_2 (since they are non-critical in both the peripheral and central DC). Instead, optimal quantities are kept in stock for the remaining α and β SKUs, where Equations 7-9 initialise the reorder level and optimal order quantity, and Equations 10-11 update such values according to the indications by other authors (Alvarez and van der Heijden, 2014; Cantini et al., 2021). Equations 10-11 avoid reordering more than twice the units required in the period of analysis ($X_{i,k,r}$) and keeping stocks of low-turnover, high-cost SKUs.

$$ROP_{i,k,r} = \left(\overline{x_{i,k,r}} * LT_{i,k}\right) + SS_{i,k,r} \tag{7}$$

$$Q_{i,k,r} = \sqrt{\frac{2 \cdot X_{i,k,r} \cdot oc_k}{h_{\%} \cdot uc_k}} \tag{8}$$

$$\begin{cases} SS_{i,k,r} = Z_{i,k,r} * \sqrt{LT_{i,k}} * \sigma\left(x_{i,k,r}\right) \; if \; k \; has \; a \; normal \; demand \\ 1 - \sum_{n=0}^{SS_{i,k,r}-1} \left[\frac{\left(\overline{x_{i,k,r}} * LT_{i,k}\right)^n}{n!} * e^{-\left(\overline{x_{i,k,r}} * LT_{i,k}\right)}\right] \geq \left(1 - SL_{i,k,r}\right) \; if \; k \; has \; a \; Poisson \; demand \end{cases} \tag{9}$$

$$Q'_{i,k,r} = \begin{cases} X_{i,k,r}, if \; Q_{i,k,r} > \left(2 * X_{i,k,r}\right) \\ Q_{i,k,r}, \; else \end{cases} \tag{10}$$

$$ROP'_{i,k,r} = \begin{cases} on - demand \; supply \; of \; k \; in \; i, \; if \; \#Ord_{i,k,r} \leq 1 \; and \; QOrd_{i,k,r} \leq 1 \\ on - demand \; supply \; of \; k \; in \; i, \; if \; \#Ord_{i,k,r} \leq 1 \; and \; uc_k \leq cost \; limit_k \\ ROP_{i,k,r}, else \end{cases} \tag{11}$$

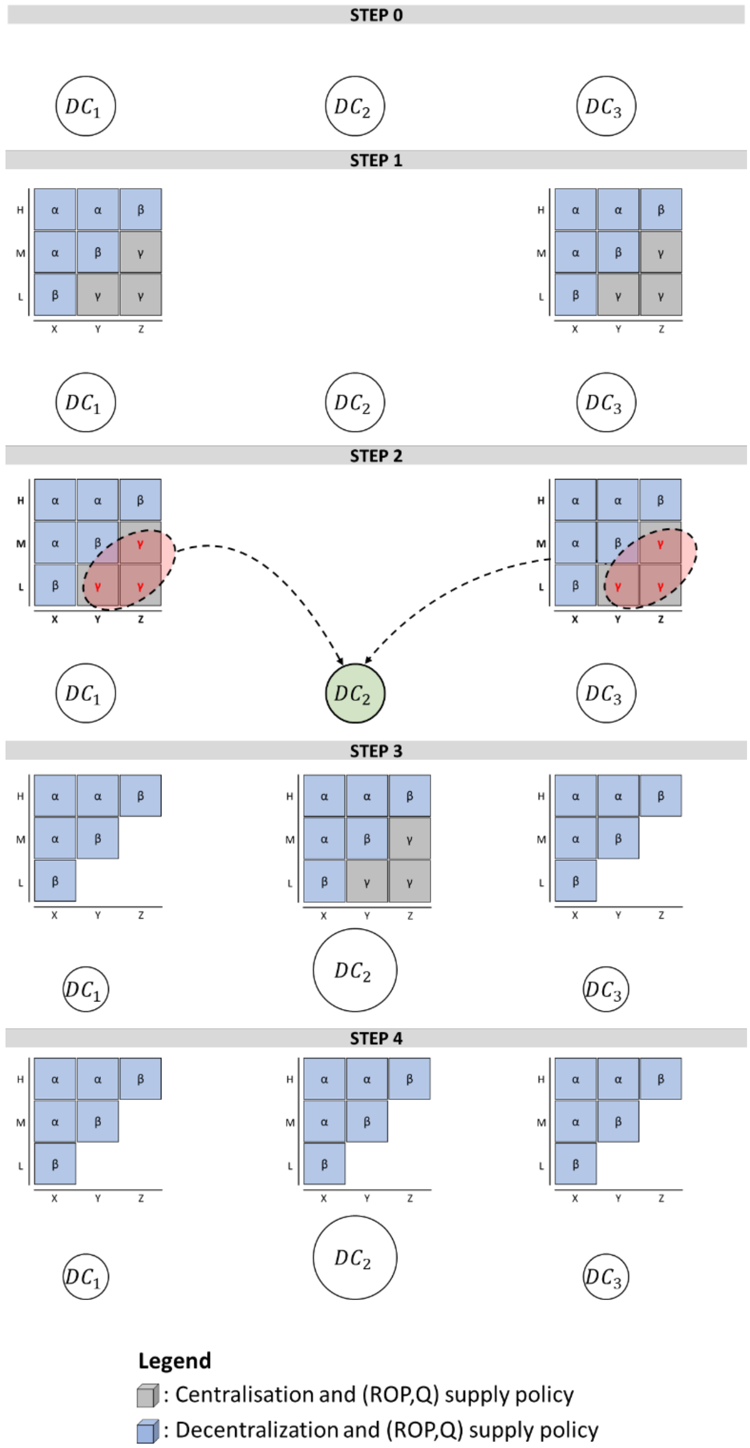

Figure 15. An example of the application of stage 1 of SP-LACE in a company with three DCs, where the central one is DC_2

Once the spare parts SC configuration has been reviewed, in **stage 2 of SP-LACE**, a mathematical model (Equations 12-21) is applied to compare the total cost of the reviewed SC with that of the starting SC (before the review process). In this way, an economic evaluation is provided where the reviewed SC configuration ($r = 1$) is considered economically beneficial over the starting one ($r = 0$) if it has a lower total cost.

$$C_{tot_r} = C_{H_r} + C_{O_r} + C_{B_r} + C_{rev_r} \tag{12}$$

$$\begin{cases} if\ C_{tot_1} \leq\ C_{tot_0} \rightarrow review\ economically\ beneficial \\ \quad else \rightarrow review\ not\ economically\ beneficial \end{cases} \tag{13}$$

$$C_{H_r} = \sum_{i=1}^{\#DCs} \sum_{k=1}^{\#SKU} h_{\%} \cdot uc_k \cdot \frac{Q'_{i,k,r}}{2} \tag{14}$$

$$C_{O_r} = \sum_{i=1}^{\#DCs} \sum_{k=1}^{\#SKU} oc_k \cdot \frac{X_{i,k,r}}{Q'_{i,k,r}} \tag{15}$$

$$C_{B_r} = \sum_{i=1}^{\#DCs} \sum_{k=1}^{\#SKU} uback_k \cdot X_{i,k,r} \cdot \left(1 - SL_{i,k,r}\right) \tag{16}$$

$$C_{rev_r} = \begin{cases} 0\ if\ r = 0 \\ C_{Sof} + C_{Disp_r} + C_{Adm_r}\ if\ r = 1 \end{cases} \tag{17}$$

$$C_{Sof} = mh \cdot tc \tag{18}$$

$$C_{Disp_r} = utrip \cdot dist \cdot \#trips_r \tag{19}$$

$$\#trips_r = \frac{\sum_{i=1}^{\#DCs} \sum_{j=1}^{\#\gamma\ SKU_{depl_{i,r}}} X_{i,j,r} * vol_k}{Cap} \tag{20}$$

$$C_{Adm_r} = \sum_{i=1}^{\#DCs} \#SKU_{supply_{i,r}} \cdot tm \cdot mh \tag{21}$$

After building the data-driven methodology (SP-LACE, which is the first outcome of RQ2), it was applied in two real companies (case studies A and B, respectively), using case study research, as introduced in Section 3.1.3. This enabled us to test and validate the results of SP-LACE in different contexts and to demonstrate which benefits are achievable by reviewing the SC configuration (in terms of average inventory levels, number of supply orders, number of backorders, holding, ordering, backorder, and SC review costs). Case study research was also useful because the developed data-driven heuristic methodology was explained to company experts, and they confirmed that it relies on a coherent set of features that properly describe the system behaviour. Finally, company experts considered the imposed simplifying assumptions acceptable and confirmed the availability of the required input parameters in the common companies' databases.

Besides testing SP-LACE on two case studies, we also compared it with a methodology presented in the previous literature (Stoll et al., 2015) and assessed its positive aspects. We selected this particular methodology for the comparison because it was the only literature heuristic methodology based on a multicriteria ABC criticality classification, which allowed for planning both the stock deployment and supply policies in spare parts SCs.

By summarising the results of the two case studies (which are described in detail in Paper 2), it emerged that SP-LACE overcomes the limitations of the selected literature methodology. SP-LACE is a quick and easy-to-use data-driven heuristic methodology that relies entirely on the analysis of objective data usually available in companies without needing to consult maintenance experts or perform qualitative analyses. This produces two beneficial side effects. First, the results of SP-LACE are unaffected by subjectivity, and mistakes related to the criticality of SKUs are avoided, thus suggestions for stock amounts are more accurate. Second, the application of SP-LACE is not time-consuming, meaning that spare parts retailers can manage thousands of SKUs and make recurrent reviews of the SC configuration. SP-LACE also enables, for the first time, an economic evaluation of the performance of the reviewed SC configuration by comparing the SC total costs before and after the review process.

Additional results of the case study research prove the importance of adopting a structured methodology to review the configuration of spare parts SCs. This can be seen in Figure 16, where the literature methodology (blue), SP-LACE (orange), and the starting (historical) company performance (gray) are compared in terms of average inventory levels (a), the number of supply orders (b), and the number of backorders (c) in all DCs and for both case studies (A and B). Figure 16 shows that SP-LACE and the literature methodology significantly improved the starting (historical) situation of companies A and B, indicating that the stock deployment and supply policies associated with SKUs so far were not aligned with customer needs. Figure 16 also highlights the advantages of SP-LACE over the literature methodology, proving that it leads to a drastic reduction in the number of supply orders and backorders, thereby reducing the consequent SC total cost (despite higher inventory levels). These advantages are achieved because SP-LACE decentralises stocks more than the literature methodology and suggests replenishing DCs through large batches and sporadic supply orders (instead of frequent one-unit lots). Finally, by keeping higher inventory levels (instead of one-unit lots), SP-LACE makes the SC more resilient compared to the literature methodology, allowing companies to better cope with unexpected demand fluctuations and prevent future stock-outs.

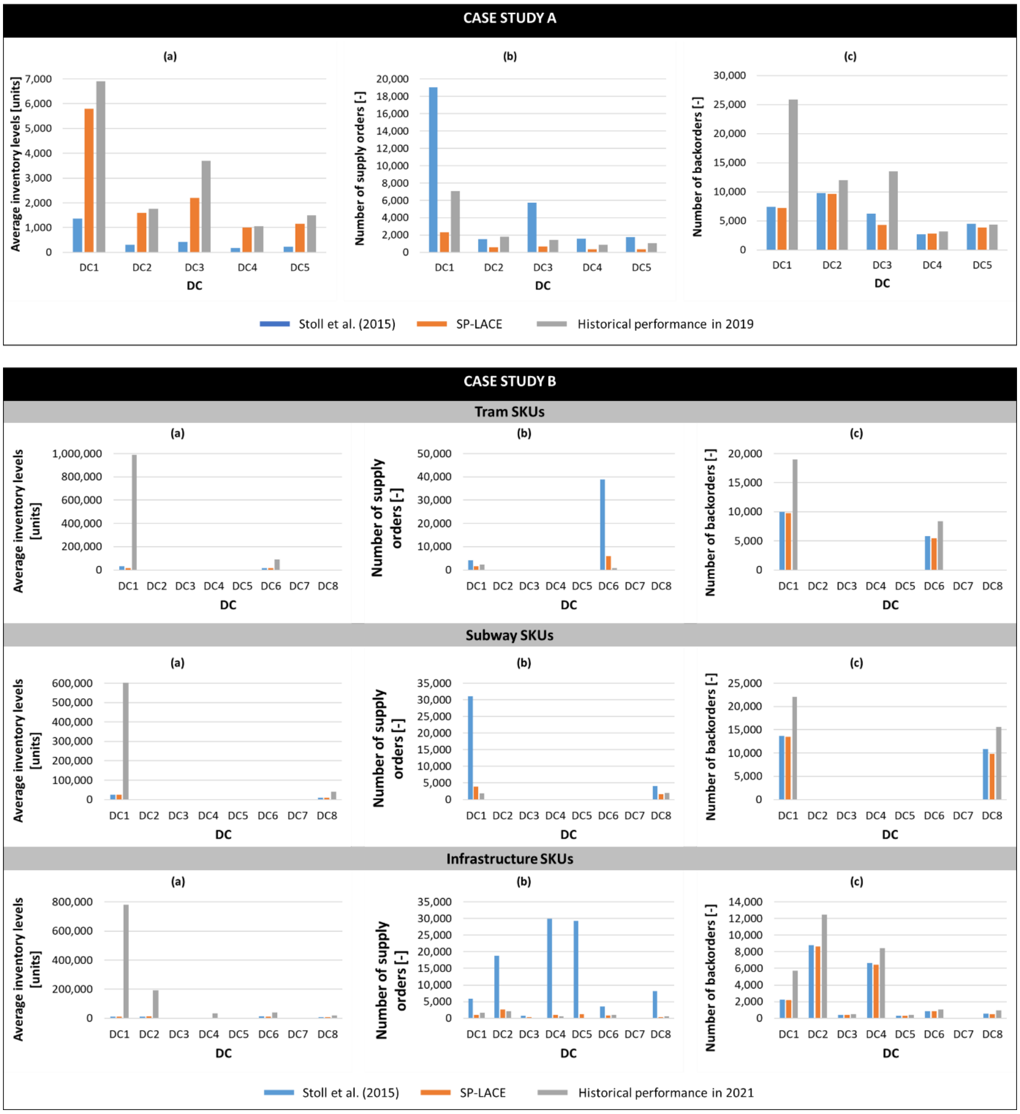

Figure 16. Total average inventory levels (a), number of orders (b), and number of backorders (c) occurring in each company DC historically (gray) and by applying SP-LACE (orange) and the literature methodology (blue), respectively

Figure 17 confirms the aforementioned results, where, for both case studies, the economic performance (C_{tot_r}) of the reviewed SC configuration ($r = 1$) is compared with the one of the starting (historical) SC configuration ($r = 0$), confronting SP-LACE, the literature methodology, and the historical company performance. In Figure 17, the results of the two case studies are presented as follows. In case study A, the review of the SC configuration was carried out not only once but twice (to show the convenience of regularly reviewing the SC configuration). For this reason, concerning case study A, in Figure 17a, reports the results of the first review (moving from the starting SC configuration to the one performed in 2019), and Figure 17b presents the results of the second review (performed after one year, moving from the SC configuration of 2019 to the one aligned with the demand of 2020). Concerning case study B, since the review of the SC configuration was performed only once (in 2021), the results of a single review are presented. Overall, Figure 17 shows that reviewing the SC configuration is convenient, producing economic savings in both case studies with respect to leaving the starting SC configuration unchanged over time. Moreover, Figure 17c shows that SP-LACE minimises not only the number of supply orders but also the backorders, thus reducing the SC total cost despite higher holding costs (due to higher inventories) than the literature methodology. Finally, SP-LACE results in less time-consumption than the literature methodology, requiring only one hour and lower review costs (C_{rev_r}) to produce results. Therefore, SP-LACE results in a data-driven heuristic methodology suitable for recurrent applications in real companies (also those with thousands of SKUs and variable spare parts demand).

SP-LACE represents the first outcome of RQ2, constituting the first heuristic methodologies proposed in this research project to review stock deployment policies (and the consequent SC configuration) in spare parts SCs. SP-LACE allows spare parts retailers to associate optimal stock deployment policies (as well as optimal supply policies) with individual SKUs and to evaluate the economic benefits of the reviewed SC configuration. Since SP-LACE showed successful results (in terms of SC costs, time-consumption, and reliability of its results) in two different case studies, this outcome was considered to produce two major contributions to this research project. First, it demonstrated, for the first time in the literature, the importance of regularly reviewing the configuration of spare parts SCs. Second, it represented the first structured, effective, quick, and easy-to-use heuristic methodology to review stock deployment policies in spare parts SCs. Therefore, this outcome can hopefully encourage spare parts retailers to review the configuration of spare parts SCs recurrently.

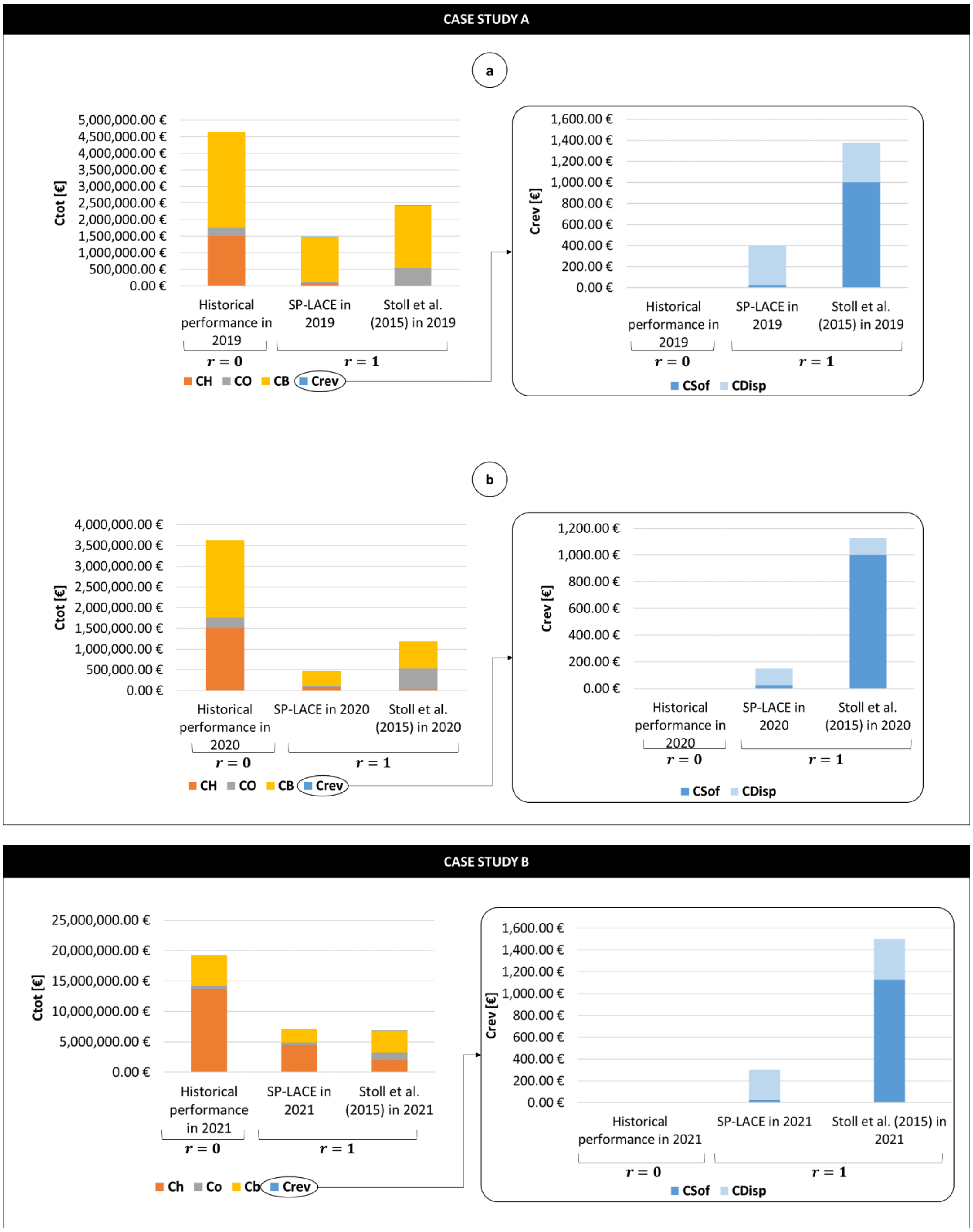

Figure 17. Economic assessment of the SC total cost (Ctot) achieved without reviewing the SC configuration (r = 0) or by reviewing it (r = 1) through SP-LACE and the literature methodology, respectively

4.3. Decision support systems (developed through heuristic methodologies) for reviewing the configuration of spare parts SCs considering different manufacturing options

After developing SP-LACE (Section 4.2), we investigated **not only RQ2 but also RQ3**. Hence, we found that the proposed data-driven heuristic methodology, despite bringing relevant contributions, provides no indication of how to match optimal stock deployment policies (centralisation, decentralisation, or hybrid stock deployment policies) with optimal spare parts manufacturing technologies (AM or CM). However, this aspect is worth investigating following claims by researchers and practitioners (see Section 1.2) that were confirmed by the SLNA.

As explained in Section 2.3, AM is an emerging technology in the field of spare parts (Ahmed et al., 2022; Frandsen et al., 2020), which has the potential to revolutionise the characteristics of SCs (Ghadge et al., 2018; Mehrpouya et al., 2022). Nevertheless, many spare parts retailers are far from adopting AM technologies in their companies, since this would imply investing capital, time, and effort to reorganise the SC without having any tools or methodologies to prove the convenience of doing so. According to Chaudhuri et al. (2021), the current literature evaluates the advantages of SCs with AM spare parts without comparing them with CM ones (which, instead, shows some advantages and constitutes the starting condition of many spare parts retailers). Therefore, there is a lack of structured methodologies to quantitatively compare the SC benefits of AM and CM spare parts and provide clear indications of when a switchover from CM to AM spare parts is cost-effective (Trancoso et al., 2018).

Based on the above observations, our efforts moved towards developing and proposing novel heuristic methodologies for reviewing the stock deployment in spare parts SCs (RQ2), attempting to compare different manufacturing options, and selecting the optimal one (RQ3). Through mathematical modelling and experimental research, we proposed two additional heuristic methodologies with which we compared the cost-effectiveness of different SC configurations in two respective situations:

- SCs where stocks of both AM and CM spare parts are assumed to be purchased from suppliers (in the form of finished products);
- SCs where stocks of CM spare parts are assumed to be purchased from suppliers, while stocks of AM spare parts are assumed to be produced in-house (by installing 3D printers inside DCs).

Each of these two additional heuristic methodologies was then used to develop a DSS, which was tasked with suggesting spare parts retailers how to review their SC configuration and selecting both the optimal stock deployment policies and spare parts manufacturing technologies. The two achieved

DSSs (as well as the heuristic methodologies followed to derive them) represent an outcome for both RQ2 and RQ3, which are presented in Subsections 4.3.1 and 4.3.2, respectively.

4.3.1. DSS (developed through a heuristic methodology) to compare different stock deployment policies with AM and CM spare parts purchased from suppliers

In this subsection, we propose a DSS (and the heuristic methodology used to achieve it) to compare the cost-effectiveness of different stock deployment policies in SCs where, according to Figure 18, both AM and CM spare parts are purchased from suppliers. This DSS (together with the heuristic methodology used to achieve it) is an outcome for both RQ2 and RQ3, and it selects, for each SKU, the optimal combination of stock deployment policy (centralisation, decentralisation, or hybrid stock deployment policies) and manufacturing option (purchase of CM or AM spare parts) that produces the minimum SC total cost. The DSS was obtained by developing a novel heuristic methodology, which is described briefly here. Paper 3 provides a more detailed explanation of both the heuristic methodology and the DSS.

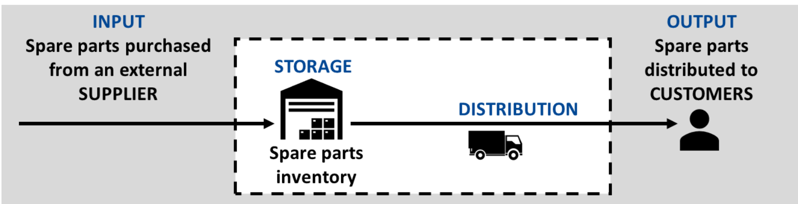

Figure 18. Control volume considered to develop the DSS in the case of both AM and CM spare parts

According to Figure 19, the DSS provided herein can be used to compare ten SC configurations obtained by considering two different manufacturing options (purchase of CM or AM spare parts from suppliers) and five alternatives of stock deployment (depicted in Figure 20, in the example of a company with six customers). Referring to the parameters reported in Table 5 and following the indications by Gregersen and Hansen (2018), the five stock deployment alternatives were defined by varying the so-called "degree of centralisation" (Equation 22), where $Deg = 0$ means decentralisation, $Deg = 0.25; 0.50;\ 0.75$ are hybrid stock deployment policies, and $Deg = 1$ means centralisation.

$$Deg = degree\ of\ centralisation = \begin{cases} 1 & full\ centralised\ SC\ configuration \\ 1 - \frac{\#DC}{\#customers} & else \end{cases} \qquad (22)$$

	Deg = 0	Deg = 0.25	Deg = 0.50	Deg = 0.75	Deg = 1
AM	1 **AM, Deg = 0** (full decentralization)	3 **AM, Deg = 0.25** (hybrid config.)	5 **AM, Deg = 0.50** (hybrid config.)	7 **AM, Deg = 0.75** (hybrid config.)	9 **AM, Deg = 1** (full centralization)
CM	2 **CM, Deg = 0** (full decentralization)	4 **CM, Deg = 0.25** (hybrid config.)	6 **CM, Deg = 0.50** (hybrid config.)	8 **CM, Deg = 0.75** (hybrid config.)	10 **CM, Deg = 1** (full centralization)

Figure 19. Matrix of the spare parts SC configurations compared in this heuristic methodology.

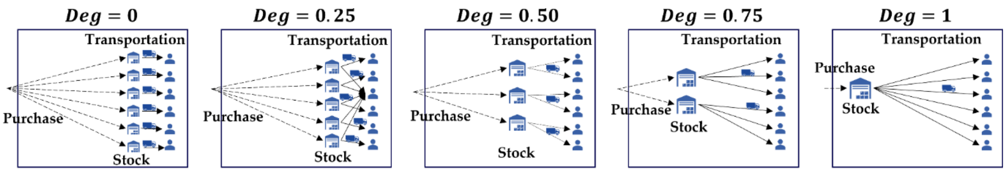

Figure 20. Schematic representation of the five stock deployment policies in the example of a company with six customers.

The achieved DSS has to be adopted for each SKU managed by a spare parts retailer. Indeed, it aims to optimise stock deployment policy and manufacturing option for each individual SKU, as suggested by Cohen et al. (2006). This DSS was developed by applying mathematical modelling and experimental research and relying on the following simplifying assumptions: (i) the costs of purchasing spare parts to replenish DCs include all the costs that the supplier incurs (Pour et al., 2016); (ii) no capacity constraints are considered for the supplier's warehouse and the DCs (Tapia-Ubeda et al., 2020); (iii) procurement lead times are assumed deterministic and dependent only on the product (not on the geographical location of DCs) (Lolli et al., 2022); (iv) spare parts demand is stochastic, following a Poisson distribution (Sherbrooke, 1968; Stoll et al., 2015); and (v) all DCs in an SC configuration are characterised by the same average transportation cost (Farahani et al., 2015). Moreover, in the case of decentralisation ($Deg = 0$), transportation costs are neglected due to the proximity between DCs and customers; (vi) no sustainability aspects are considered (Zijm et al., 2019); (vii) no lateral transhipments are admitted (Schwarz, 1973); (viii) only variable costs are considered (not assessing investment costs in facilities) since we are reviewing the configuration of existing SCs; (ix) spare parts transportation costs are calculated by assuming that only one spare part is delivered per trip. This hypothesis is considered acceptable because spare parts demand follows a Poisson distribution, also known as the law of rare events; (x) a continuous (ROP, Q) inventory policy is used to manage stocks in DCs, where ROP is the reorder point and Q is the optimal order quantity (Fathi et al., 2021; Sapna Isotupa, 2006); and (xi) the period considered to develop the analysis is one year (Daskin et al., 2002).

Table 5. List of parameters for the DSS. They refer to a single SKU.

Parameter	Description	Unit measure
	Input parameters	
i	Considered SC design. i can assume integer values between 1 and 10 according to Figure 19	-
j	Manufacturing technology of the purchased spare parts (AM or CM)	-
$\#customers$	Number of customers served by the company	-
$ELT\ SL$	Expected service level. It is given by the ratio between the demands for SKU answered on time and the overall number of demands for SKU answered (Ivanov, 2021)	-
$\overline{D}_{1\ customer}$	Average annual demand for SKU emitted by one customer	units/time
Deg_i	Degree of centralisation in SC configuration i. According to Figure 19, Deg_i is 0 if $i = 1$ or 2, is 0.25 if $i = 3$ or 4, is 0.5 if $i = 5$ or 6, is 0.75 if $i = 7$ or 8, while is 1 if $i = 9$ or 10	-
$et\ central_i$	Unitary transportation cost from the central DC to customers. It only refers to centralised SC configurations ($i = 9$ or $i = 10$)	€/transportation
$uback$	Unitary cost of one backorder of SKU	€/backorder
L_j	Procurement lead time needed by the supplier to deliver each SKU to DCs	time
uc_j	Unitary cost of purchasing the j-th SKU from the supplier	€/unit
mh	Hourly labour cost	€/time
ot	Average time needed to send one supply order to replenish DCs	time
$h_{\%}$	Holding cost rate for keeping inventory of SKU	time^{-1}
	Cost items considered	
$Ctot_i$	Spare parts SC total costs (it is related to the considered SKU and the considered interval of analysis that is one year)	€/time
$PC_{i,j}$	Cost of purchasing spare parts	€/time
$OC_{i,j}$	Cost of placing supply orders	€/time
$HC_{i,j}$	Cost of holding inventory	€/time
ETC_i	Cost of transporting spare parts from DCs to customers	€/time
BC_i	Cost of backorders	€/time
	Other parameters	
$\#DC_i$	Number of DCs in the SC	-
$\overline{Dtot_i}$	Average annual demand in each DC	units
$\#orders_{i,j}$	Average number of supply orders	-
$Q_{i,j}$	Economic order quantity for replenishing SKUs in DCs	units
$I_{i,j}$	Average inventory in each DC	units
$SS_{i,j}$	Safety stocks in each DC, calculated to compensating demand fluctuations at least to ensure the desired service level.	units
$\overline{Dtot\ in\ lead\ time_{i,j}}$	Average demand of spare parts during the procurement lead time	units/time
et_i	Unitary transportation costs	€/transportation
$et\ decentral_i$	Unitary transportation costs for decentralised and hybrid stock deployment policies	€/transportation
$\#backorders_i$	Average number of backorders	backorders

To achieve the DSS, a heuristic methodology was devised, comprising four steps. In ***Step 1***, mathematical modelling was applied (Equations 23-39) to compare the cost-effectiveness of different SC configurations with different stock deployment policies and spare parts manufacturing options, thus defining the combination with the minimum cost.

$$min[Ctot_i]\ with\ i = 1, 2, \dots, 10 \tag{23}$$

$$Ctot_i = PC_{i,j} + OC_{i,j} + HC_{i,j} + ETC_i + BC_i \tag{24}$$

$$PC_{i,j} = uc_j * \overline{Dtot_i} * \#DC_i \tag{25}$$

$$\#DC_i = \begin{cases} [(1 - Deg_i) * \#customers]^+ & if\ i = 1, 2, \dots, 8 \\ 1 & if\ i = 9, 10 \end{cases} \tag{26}$$

$$\overline{Dtot_i} = \begin{cases} \left(\frac{\overline{D}_{1\ customer} * \#customers}{\#DC_i}\right) & if\ i = 1, 2, \dots, 8 \\ (\#customers * \overline{D}_{1\ customer}) & if\ i = 9, 10 \end{cases} \tag{27}$$

$$OC_{i,j} = (mh * ot * \#orders_{i,j}) * \#DC_i \tag{28}$$

$$\#orders_{i,j} = \frac{\overline{Dtot_i}}{Q_{i,j}} \tag{29}$$

$$Q_{i,j} = \sqrt{\frac{2 * \overline{Dtot_i} * mh * ot}{uc_j * h_{\%}}} \tag{30}$$

$$HC_{i,j} = (uc_j * h_{\%} * I_{i,j}) * \#DC_i \tag{31}$$

$$I_{i,j} = \frac{Q_{i,j}}{2} + SS_{i,j} \tag{32}$$

$$1 - \sum_{n=0}^{SS_{i,j}-1} \left[\frac{\left(\overline{Dtot\ in\ lead\ time_{i,j}}\right)^n}{n!} * e^{-\overline{Dtot\ in\ lead\ time_{i,j}}}\right] \geq (1 - ELT\ SL) \tag{33}$$

$$\overline{Dtot\ in\ lead\ time_{i,j}} = \overline{Dtot_i} * L_j \tag{34}$$

$$ETC_i = (et_i * \overline{Dtot_i}) * \#DC_i \tag{35}$$

$$et_i = \begin{cases} et\ decentral_i & if\ i = 1, 2, \dots, 8 \\ et\ central_i & if\ i = 9, 10 \end{cases} \tag{36}$$

$$et\ decentral_i = et\ central_i * (0.7644 * Deg_i^2 + 0.2009 * Deg_i + 0.0161) \tag{37}$$

$$BC_i = (uback * \#backorders_i) * \#DC_i \tag{38}$$

$$\#backorders_i = [(1 - ELT\ SL) * \overline{Dtot_i}]^+ \tag{39}$$

Subsequently, in Steps 2-4, experimental research was leveraged. In ***Step 2***, an ANOVA with Main Effect Plot was performed to determine the most relevant input parameters of the mathematical model, thus excluding from the next steps those with a negligible impact on the selection of the optimal SC configuration. To this end, a preliminary parametric analysis was carried out by associating the input parameters of Table 5 with a range of three realistic discrete values (Table 6) and differentiating the cost items according to AM or CM manufacturing. Table 6 does not refer to mh, ot, $h_{\%}$, and i since mh, ot, $h_{\%}$ were assumed fixed (30 €/h, 10 minutes, and 25%, respectively), while i already had predefined values. Then, the admissible values of the input parameters were combined, generating the so-called "*SC scenarios*" (a set of input values). Next, each SC scenario was given as an input for the mathematical model of Step 1, defining its respective optimal SC configuration. Finally, the results were subjected to an ANOVA using Minitab software, where the values composing the SC scenarios were indicated as input factors, and their associated optimal SC configurations were indicated as responses. Figure 21 shows the ANOVA results. It emerged that three out of nine input parameters (L_{AM}, L_{CM}, and $ELT\ SL$) have a negligible impact on the process of selecting the optimal spare parts SC configuration, providing a curve in the Main Effects Plots that is almost horizontal.

These parameters were not considered for building the DSS, while the remaining six were considered in the next steps of this heuristic methodology.

Table 6. Parameters and values of the discretised parametric analysis

Input parameter	Admissible values	Unit measure	Source used to define admissible values
$\#customers$	5; 53; 100	-	Authors' experience
$ELT\ SL$	0.85; 0.92; 0.99	-	Authors' experience
$\overline{D}_{1\ customer}$	1; 4; 7	units/year	(Knofius et al., 2021)
$et\ central_i$	100; 1,050; 2,000	€/transportation	Authors' experience
$uback$	1,000; 50,500; 100,000	€/backorder	(Peron et al., 2021)
L_{AM}	1; 2.5; 4	weeks	(Knofius et al., 2021)
L_{CM}	4; 15; 26	weeks	(Knofius et al., 2021)
uc_{AM}	100; 1,300; 2'500	€/unit	(Knofius et al., 2021)
uc_{CM}	10; 1,255; 2,500	€/unit	(Knofius et al., 2021)

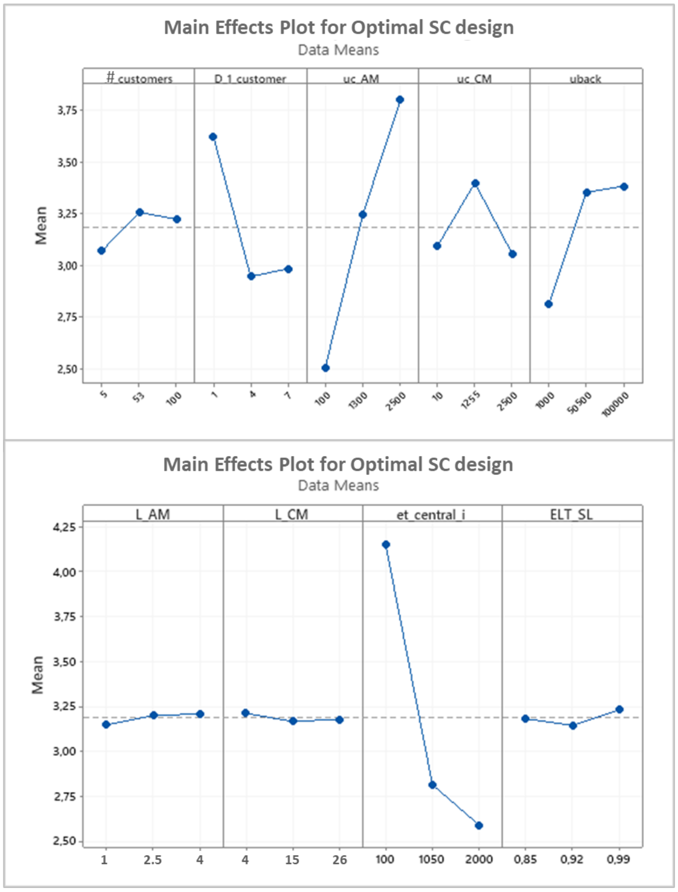

Figure 21. Results of the ANOVA (Main Effects Plots).

In ***Step 3***, another parametric analysis was performed to investigate a sample of 10,000 realistic SC scenarios (i.e., case studies of spare parts SCs characterised by different spare parts demand, purchasing costs, transportation costs, backorder costs, and required service levels). The SC scenarios were collected by associating the relevant input parameters (emerged in Step 2) with Sobol quasi-random values (following the procedure explained in Section 3.1.4), according to the admissible ranges listed in Table 7. Then, each SC scenario was submitted to the mathematical model of Step 1, and its related optimal SC configuration was determined.

Table 7. Values considered in the Sobol-based parametric analysis. The range extreme values are based on Table 6

Input parameter	Range of admissible values	Unit measure
$\#customers$	integers between 5 and 100	-
$ELT\ SL$	floats between 0.85 and 0.99	-
$\bar{D}_{1\ customer}$	integers between 1 and 7	units/year
$et\ central_i$	floats between 100 and 2,000	€/transportation
$uback$	floats between 1,000 and 100,000	€/backorder
L_{AM}	integers between 1 and 4	weeks
L_{CM}	integers between 4 and 26	weeks
uc_{AM}	floats between 100 and 2,500	€/unit
uc_{CM}	floats between 10 and 2,500	€/unit

In ***Step 4***, the desired DSS was obtained by feeding and training a decision tree algorithm with the results of the Sobol-based parametric analysis (following the machine learning procedure explained in Section 3.1.4). Figure 22 depicts the achieved DSS, which was pruned (more indications are provided in Paper 3), searching for a trade-off between accuracy ($A = 77\%$, Equation 2) and user-friendliness (i.e., few questions to be answered to get a solution). Finally, the performance of the achieved DSS was evaluated (Equations 3-5), which are reported in Figure 22.

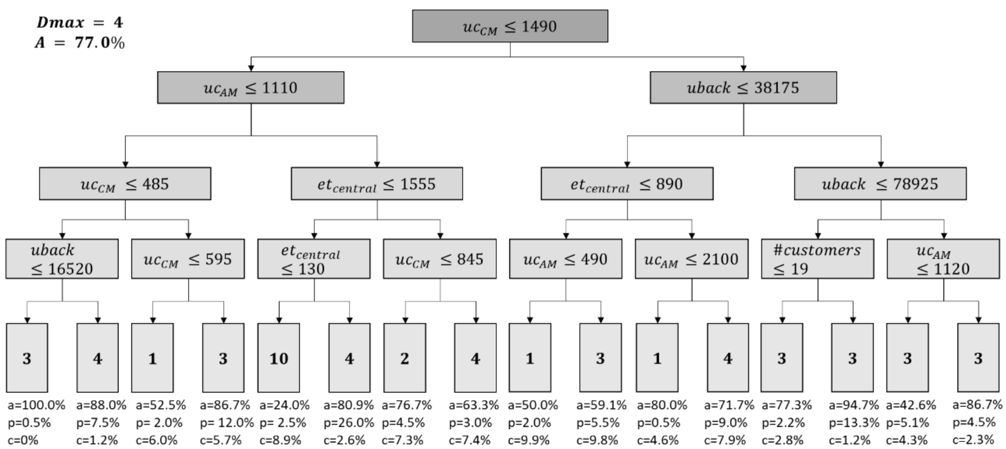

Figure 22. Achieved DSS in the form of a decision tree. The numbers inside each leaf refer to Figure 19

To conclude this subsection, we developed a heuristic model and achieved a DSS, which suggests the optimal (cost-effective) SC configuration among those listed in Figure 19, optimising two aspects simultaneously:

- the stock deployment policies of individual SKUs, opting for centralisation ($Deg = 1$), decentralisation ($Deg = 0$), or hybrid stock deployment policies ($Deg = 0.25; 0.50;\ 0.75$);
- the manufacturing option of each SKU, indicating whether to purchase AM or CM spare parts.

The DSS shows that the most recommended spare parts SC configurations are those with $Deg_i = 0.25$ (SC configurations 3 and 4 in Figure 19, which are suggested in 11 out of 16 leaves of the tree). Conversely, the DSS never suggests SC configurations 5-9 of Figure 19, indicating as not cost-effective the SCs with Deg_i of 0.50 and 0.75, as well as the total centralisation of AM spare parts. Given these results, this study demonstrates the importance of considering hybrid stock deployment policies in the analysis, and not just a comparison of the SCs with total centralisation or decentralisation. In particular, SC configuration 3 with AM spare parts and $Deg_i = 0.25$ appears cost-effective when uc_{CM} is higher than 1,490 €/unit and $uback$ is higher than 38,175 €/backorder. In such a case, the unitary cost of purchasing AM spare parts is similar to (or lower than) the CM one, making AM spare parts preferable. Moreover, in such a case, a hybrid stock deployment policy with a low degree of decentralisation (0.25%) reduces backorders, benefiting from the risk-pooling effect (the demand is aggregated in a few DCs), while keeping delivery times and costs lower than in a fully centralised SC configuration.

The achieved DSS can be considered reliable based on its KPIs (A, a, p, and c). It is characterised by some leaves with a very high accuracy ($a >$ 90%), which guarantees the reliability of the predictions. Moreover, despite presenting some leaves with a low accuracy ($a < 50\%$, which may seem insufficient to trust the DSS), the increase of cost (c) that spare parts retailers should pay in the case of a wrong decision is always less than 10% (often even below 5%). This result means that an incorrect prediction of the DSS has an impact on the company's economy, which is almost negligible with respect to the one that the optimal spare parts SC configuration (correct prediction) would imply. Hence, the low value of c makes it easier for spare parts retailers to accept the DSS, even when the accuracy of its leaves is not very high.

The DSS is the main outcome of this subsection, answering both RQ2 and RQ3. However, two additional contributions of this work can be identified as follows. First, a heuristic model has been developed where, in particular, Equations 23-39 have been provided, for the first time in the literature, to quantitatively compare SC configurations with different stock deployment policies and manufacturing options. Second, it has been proved through a parametric analysis and an ANOVA that the procurement lead time of spare parts (L_j) and the expected service level ($ELT\ SL$) have a negligible impact on the performance of an SC configuration. Therefore, these parameters, which are commonly considered when spare parts retailers make strategic decisions regarding their SC configurations, do not have a relevant effect on the considered decision-making process.

4.3.2. DSS (developed through a heuristic methodology) to compare different stock deployment policies with CM spare parts purchased from suppliers and AM spare parts produced in-house

To complement the DSS in Section 4.3.2, another DSS was proposed, which was achieved after developing a heuristic model. This DSS compares the cost-effectiveness of different stock deployment policies in SCs, where, according to Figure 23, the replenishment of DCs can be performed by purchasing CM spare parts from suppliers (in the form of finished products), or by producing AM spare parts in-house (namely, installing 3D printers in DCs). As a result, this DSS supports spare parts retailers in defining, for each SKU, the combination of stock deployment policy (considering the same alternatives of Figure 20) and manufacturing option (purchase of CM spare parts or production of AM ones) that produces the minimum SC total cost. The achieved DSS (together with the heuristic methodology used to achieve it) represents an outcome for both RQ2 and RQ3, where both the heuristic model and the DSS are briefly described below. Paper 4 provides a more detailed explanation of both the heuristic methodology and the DSS.

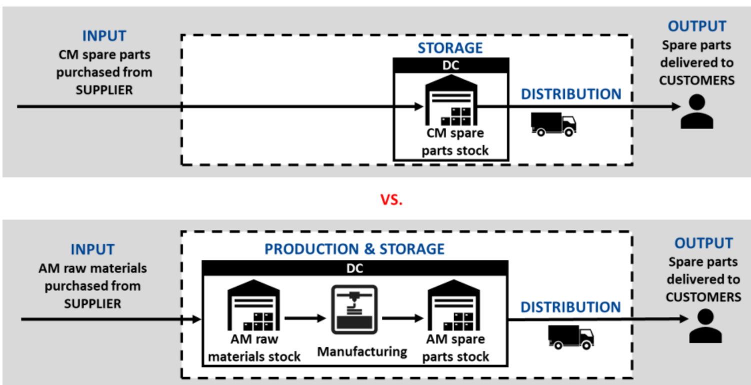

Figure 23. Control volume (within dashed lines) considered to develop the DSS in the case of CM and AM spare parts, respectively

Unlike the DSS in Subsection 4.3.1, the DSS herein provided does not consider a single SKU per time. Rather, it optimises the management of multiple SKUs at the same time, and it assumes a spare parts retailer who currently manages CM spare parts but is interested in evaluating a switchover to AM as a starting condition. The spare parts retailer has three possible alternatives to consider: (i) continue purchasing from suppliers SKUs as CM spare parts (which we refer to as "single-sourcing CM"), (ii) replace the purchase of CM spare parts with AM in-house production (which we refer to as "single-sourcing AM"), or (iii) produce some SKUs in-house using AM, while purchasing others in CM (which we refer to as "dual-sourcing CM/AM"). In this context, the DSS was achieved by, first, supporting spare parts retailers in optimising the starting stock deployment policies for CM spare parts and then, splitting CM SKUs into groups (from now on referred to as ''sub-sets"), which put together all SKUs associated with the same degree of centralisation (Equation 22). Finally, by applying mathematical modelling and experimental research to each sub-set, we achieved a DSS (one per sub-set), which can be used to compare 11 different SC configurations, as summarised in Figure 24. Figure 24 refers, as an example, to the sub-set of CM SKUs associated with an initial degree of centralisation equal to zero, but it can be easily extended to other sub-sets following the indications provided in the caption.

We are aware of the simplifications considered by splitting SKUs into sub-sets (i.e., the SC design is not optimised by considering all SKUs together, but by dividing them into sub-sets and looking for the optimum within each sub-set). However, we consider this choice acceptable for the following reasons. Other authors (Daskin et al., 2002; Patriarca et al., 2016) have proposed exact optimisation models to optimise stock deployment policies in two-echelon SCs (focusing solely on CM spare parts without considering AM ones). However, the proposed exact optimisation models require Lagrangian relaxations, branch-and-bound algorithms, and heuristic forcing rules to be solved, leading to solutions that are local optimums (not necessarily absolute ones). Therefore, having to accept a local optimum solution in any case, we simplify the problem from the very beginning, taking advantage of this simplification to achieve a quick, user-friendly heuristic model.

STARTING CONDITION: sub-set of SKUs purchased as CM spare parts and deployed with $Deg = 0$	STOCK DEPLOYMENT POLICIES				
MANUFACTURING TECHNOLOGIES	$Deg = 0$	$Deg = 0.25$	$Deg = 0.50$	$Deg = 0.75$	$Deg = 1$
Single-sourcing CM	0 Keep on purchasing all SKUs as CM spare parts, and mantain the initial stock deployment policy characterising the sub-set (Deg=0)	-	-	-	-
Single-sourcing AM	1 Produce all SKUs as AM spare parts, and mantain the initial stock deployment policy with Deg=0	2 Produce all SKUs as AM spare parts, and change the stock deployment policy adopting Deg=0.25	3 Produce all SKUs as AM spare parts, and change the stock deployment policy adopting Deg=0.50	4 Produce all SKUs as AM spare parts, and change the stock deployment policy adopting Deg=0.75	5 Produce all SKUs as AM spare parts, and change the stock deployment policy adopting Deg=1
Dual-sourcing CM/AM	6 Produce some SKUs with AM, adopting Deg=0 as stock deployment policy. Keep on purchasing the other SKUs as CM spare parts, mantaining the initial stock deployment policy (Deg=0)	7 Produce some SKUs with AM, adopting Deg=0.25 as stock deployment policy. Keep on purchasing the other SKUs as CM spare parts, mantaining the initial stock deployment policy (Deg=0)	8 Produce some SKUs with AM, adopting Deg=0.50 as stock deployment policy. Keep on purchasing the other SKUs as CM spare parts, mantaining the initial stock deployment policy (Deg=0)	9 Produce some SKUs with AM, adopting Deg=0.75 as stock deployment policy. Keep on purchasing the other SKUs as CM spare parts, mantaining the initial stock deployment policy (Deg=0)	10 Produce some SKUs with AM, adopting Deg=1 as stock deployment policy. Keep on purchasing the other SKUs as CM spare parts, mantaining the initial stock deployment policy (Deg=0)

Figure 24. SC configurations investigated by considering different manufacturing technologies and stock deployment policies. This figure refers to the sub-set of SKUs with Deg = 0. However, it can be extended to other sub-sets by moving to the right the SC design number zero.

The achieved DSS (one per each sub-set) relies on the indexes, parameters, and variables listed in Table 8 and considers the following simplifying assumptions: (i) no capacity constraints are considered for the supplier's warehouse and the DCs (Tapia-Ubeda et al., 2020); (ii) procurement lead times are assumed deterministic and dependent only on the product (not on the geographical location of DCs) (Lolli et al., 2022); (iii) spare parts demand is stochastic, following a Poisson distribution (Sherbrooke, 1968; Stoll et al., 2015); and (iv) all DCs in an SC configuration are characterised by the same average transportation cost. Moreover, transportation costs are calculated by assuming that only one spare part is distributed in each trip since a Poisson demand is considered, which is known as the law of rare events; (v) a continuous (ROP, Q) inventory policy is used to manage both stocks of finished products and AM raw materials, where ROP is the reorder point and Q is the optimal order quantity (Song and Zhang, 2020); (vi) the purchase of CM spare parts and the production of the AM ones are performed according to a make-to-stock policy, while the on-demand production of AM spare parts is precluded due to current AM technological limits related to high production times (Kumbhar and Mulay, 2018; Sgarbossa et al., 2021); (vii) no sustainability aspects and risks affecting different SC designs are considered, excluding reverse logistics, environmental aspects, lateral transhipments, and risks connected to the protection of intellectual property rights and liability of Computer-Aided Design (CAD) projects (Zijm et al., 2019); (viii) all AM SKUs are considered to be made of the same AM raw material (Mehrpouya et al., 2022; Priarone et al., 2021); and (ix) all SKUs are supposed producible with both AM and CM (Chaudhuri et al., 2021); (x) fixed investment costs for purchasing/renting facilities are not considered since we are reviewing the configuration of existing SCs; (xi) the period considered to develop the analysis is one year (Daskin et al., 2002).

Table 8. List of parameters for the DSS

Index	Description	Unit of measure
$\boldsymbol{i}$	Identifier of the considered SC design. i assumes integer values between 0 and 10 according to Figure 24	-
$\boldsymbol{d}$	Considered DC. Given the analysed type of SC design (CM, AM, or CM/AM), d assumes integer values between 1 and $\#DC_{CM}$ or $\#DC_{AM}$	-
$\boldsymbol{j}$	Manufacturing technology of each SKU. j can be CM or AM	-
$\boldsymbol{k}$	Considered SKU. k assumes integer values between 1 and K	-
Input parameter	**Description**	**Unit of measure**
$\boldsymbol{K}$	Total number of SKUs in the considered sub-set	-
$\boldsymbol{\#customers}$	Number of customers served by the spare part retailer	-
$\boldsymbol{\bar{D}_{1c_k}}$	Average annual demand emitted by one customer for each SKU	units/time
$\boldsymbol{Deg_{CM}}$	Degree of centralisation of CM spare parts. It can assume specific values according to Figure 20	-
$\boldsymbol{Deg_{AM}}$	Degree of centralisation of AM spare parts. It can take specific values according to Figure 20	-
$\boldsymbol{t\ central}$	Unitary transportation cost to deliver an SKU from the central DC ($Deg_{CM} = 1$ or $Deg_{AM} = 1$) to a customer	€/transportation
$\boldsymbol{c_{b_k}}$	Unitary backorder cost of each SKU	€/backorder
$\boldsymbol{L_k}$	Procurement lead time required by supplier to deliver a CM SKU	time
$\boldsymbol{uc_k}$	Unitary purchase cost of a CM SKU. It includes all costs that the supplier incurs (e.g., production, quality tests, equipment, etc.) together with the desired profit margins (Pour et al., 2016)	€/unit
$\boldsymbol{oc}$	Unitary cost of a supply order. It is given by the product between the average time required to issue one supply order and the hourly labour cost in DCs	€/order
$\boldsymbol{h_{\%_d}}$	Holding cost rate for keeping SKUs in a DC during the period of analysis. It includes variable costs of facilities, and risks connected to opportunity costs and stocks obsolescence (Khajavi et al., 2014)	$time^{-1}$
$\boldsymbol{n_k}$	Constant which, multiplied by the purchase cost of a CM SKU, returns the production cost of an equivalent AM SKU (Knofius et al., 2021)	-
$\boldsymbol{L_{raw}}$	Procurement lead time required by supplier to deliver AM raw material	time
$\boldsymbol{SL}$	Desired spare parts service level. It is the same for all SKUs, being the ratio between the number of demands answered on time for each SKU and the total number of demands answered for that SKU (Ivanov, 2021)	-
$\boldsymbol{SL_{raw}}$	Desired service level for AM raw material	-
$\boldsymbol{den_{raw}}$	Density of AM raw material	Kg/m^3
$\boldsymbol{unit_{raw}}$	Unitary pack size according to which AM raw material is purchased (e.g., a metal can containing 20 kg of powder (Sandvik AB, 2022))	unit raw
$\boldsymbol{Cap_{3DP}}$	Average annual production capacity of a 3D printer. It is expressed in terms of production hours, being related to the opening time of DCs and the working hours of manpower (Basto et al., 2019)	time
$\boldsymbol{Leas}$	Annual leasing cost of a 3D printer. It is supposed to be bought on leasing to allow refurbishments when AM technology advances	€/time
Variable	**Description**	**Unit of measure**
$\boldsymbol{C_{tot_i}}$	Annual cost of a SC design	€/time
$\boldsymbol{C_{CM_{d,k}}}$	Annual cost of a CM SKU in a DC	€/time
$\boldsymbol{C_{AM_{d,k}}}$	Annual cost of an AM SKU in a DC	€/time
$\boldsymbol{C_{P_{d,k}}}$	Annual cost of purchasing a CM SKU (from the supplier), to replenish a DC	€/time
$\boldsymbol{C_{O_{d,k}}}$	Annual ordering cost for supplying a CM SKU in a DC	€/time
$\boldsymbol{C_{H_{d,k}}}$	Annual holding cost for keeping stocks of a SKU in a DC	€/time
$\boldsymbol{C_{T_{d,k}}}$	Annual transportation cost for delivering a SKU to customers	€/time

$C_{B_{d,k}}$	Annual backorder cost of a SKU in a DC	€/time
$C_{Praw_{d,k}}$	Annual cost for purchasing the AM raw material needed to produce a specific AM SKU in a DC	€/time
$C_{Hraw_{d,k}}$	Annual holding cost for keeping in a DC the specific quantity of AM raw material required to produce a SKU	€/time
$C_{Oraw_{d,k}}$	Annual ordering cost for supplying the AM raw material which is required to produce a certain SKU in a DC	€/time
$C_{Prod_{d,k}}$	Annual AM production cost in a DC. It includes costs for creating CAD projects, setting up 3D printers, keeping manpower, printing spare parts, and performing quality tests	€/time
$\#3DP_d$	Number of 3D printers to be installed in each DC	-
C_{print_d}	Annual leasing cost of 3D printer(s) installed in a DC	€/time
$C_{3DP_{d,k}}$	Annual leasing cost of 3D printer(s) installed in a DC, where the cost has been allocated to each individual SKU	€/time
F_d	Number of SKUs for which AM production is allowed at the current loop iteration. F can assume integer values between 0 and K, where in the first loop iteration $F = K$ (AM allowed for all SKUs), while in the next loop iterations F is reduced if, for some SKUs, AM appears not economically convenient in respect with CM	-
$\overline{D_{d,k}}$	Average annual demand of the considered SKU in each DC	units
$\#DC_{CM}$	Number of DCs in which SKUs should be stored if they were purchased as CM spare parts	-
$\#DC_{AM}$	Number of DCs in which SKUs should be stored if they were produced as AM spare parts	-
oc	Unitary cost of issuing one supply order	€/order
$\#ord_{d,k}$	Average number of supply orders for each SKU in each DC	-
$Q_{d,k}$	Optimal order quantity to replenish SKUs in a DC	units
$SS_{d,k}$	Safety stocks of each SKU in a DC. It corresponds to the smallest value that compensates demand fluctuations during the procurement lead time and ensures the desired service level	units
$h_{d,k}$	Unitary holding cost for keeping stocks of spare parts in a DC	€/time
$\overline{Dlt_{d,k}}$	Demand for each SKU received during the procurement lead time	units
z_{raw}	If the demand for AM raw materials follows a normal distribution, SL_{raw} is associated with the service factor (z_{raw}) of the corresponding standardised normal distribution	-
$I_{d,k}$	Average inventory of each SKU in a DC	units
t_d	Unitary transportation cost in a DC	€/transportation
$t\ decentral_d$	Unitary transportation cost to deliver an SKU from a decentralised DC ($Deg_{CM} > 1$ or $Deg_{AM} > 1$) to a customer	€/transportation
$\#backorders_{d,k}$	Average number of backorders of a SKU in a DC	-
uc_{raw}	Unitary purchase cost of AM raw material required to produce each specific SKU	€/unit raw
$\overline{q_{raw_k}}$	Average quantity of AM raw material required to produce an AM SKU	units raw
vol_k	Volume of each SKU	m^3
$prod_k$	Unitary AM production cost of a SKU, which is an AM spare part	€/unit
$\#ord_{raw_{d,k}}$	Number of supply orders issued in a DC to replenish the specific quantity of AM raw material required to produce a SKU	orders
$\#ord_{TOT\ raw_d}$	Total number of supply orders issued for supplying AM raw material (required to produce all AM SKUs) in a DC	orders
$\overline{D_{raw_d}}$	Average amount of AM raw material required to produce all SKUs in a DC	units raw
Q_{raw_d}	Optimal order quantity adopted to replenish AM raw material in a DC	units raw
$h_{raw_{d,k}}$	Unitary holding cost for keeping stocks of AM raw material in a DC	€/time
$I_{raw_{d,k}}$	Average inventory of AM raw material determined by an AM SKU in a DC	units raw
I_{TOTraw_d}	Average inventory of AM raw material determined by all AM SKUs in a DC	units raw
SS_{raw_d}	Safety stocks of AM raw material required to compensate demand fluctuations and ensure the desired service level in a DC	units raw
$\overline{Dlt_{raw_d}}$	Demand for AM raw material received during the procurement lead time	units raw
$p.time_k$	Number of production hours that 3D printers work to produce one unit of each AM SKU	time/unit

$\boldsymbol{time_{tot_d}}$	Total number of production hours required to produce all AM SKUs	time
$\overline{\boldsymbol{D}_{1c}}$	Arithmetic mean of the values assumed by $\overline{D}_{1c_k}$ for all SKUs	units/time
$\overline{\mathbf{c_b}}$	Arithmetic mean of the values assumed by c_{b_k} for all SKUs	€/backorder
$\overline{\boldsymbol{L}}$	Arithmetic mean of the values assumed by L_k for all SKUs	time
$\overline{\boldsymbol{n}}$	Arithmetic mean of the values assumed by n_k for all SKUs	-
$\overline{\boldsymbol{uc}}$	Arithmetic mean of the values assumed by uc_k for all SKUs	€/unit

As already introduced, to develop the DSS, we considered spare parts retailers who buy CM spare parts from suppliers and deliver them to customers (Heinen and Hoberg, 2019). Moreover, such spare parts retailers are considered to have already optimised the stock deployment policies of CM spare parts, dividing SKUs into sub-sets. However, if spare parts retailers have not yet accomplished this task, this is not a limitation, since they can do so by consulting Figure 25. In fact, to enable any spare parts retailer to achieve the required starting conditions, we applied the methodology by Cantini et al. (2022) (described in Section 4.3.1), focusing on CM spare parts (i.e., excluding AM variables). Hence, we derived Figure 25, which guides the optimisation procedure, indicating under which conditions (combinations of input parameters listed in Table 8) each CM SKU has to be associated with different stock deployment policies. Figure 25 suggest splitting CM SKUs into only three sub-sets (characterised by Deg_{CM} equal to 0, 0.25, and 0.50, respectively), underlining as not cost-effective for CM spare parts the other stock deployment policies of Figure 20 (with Deg_{CM} equal to 0.75 and 1).

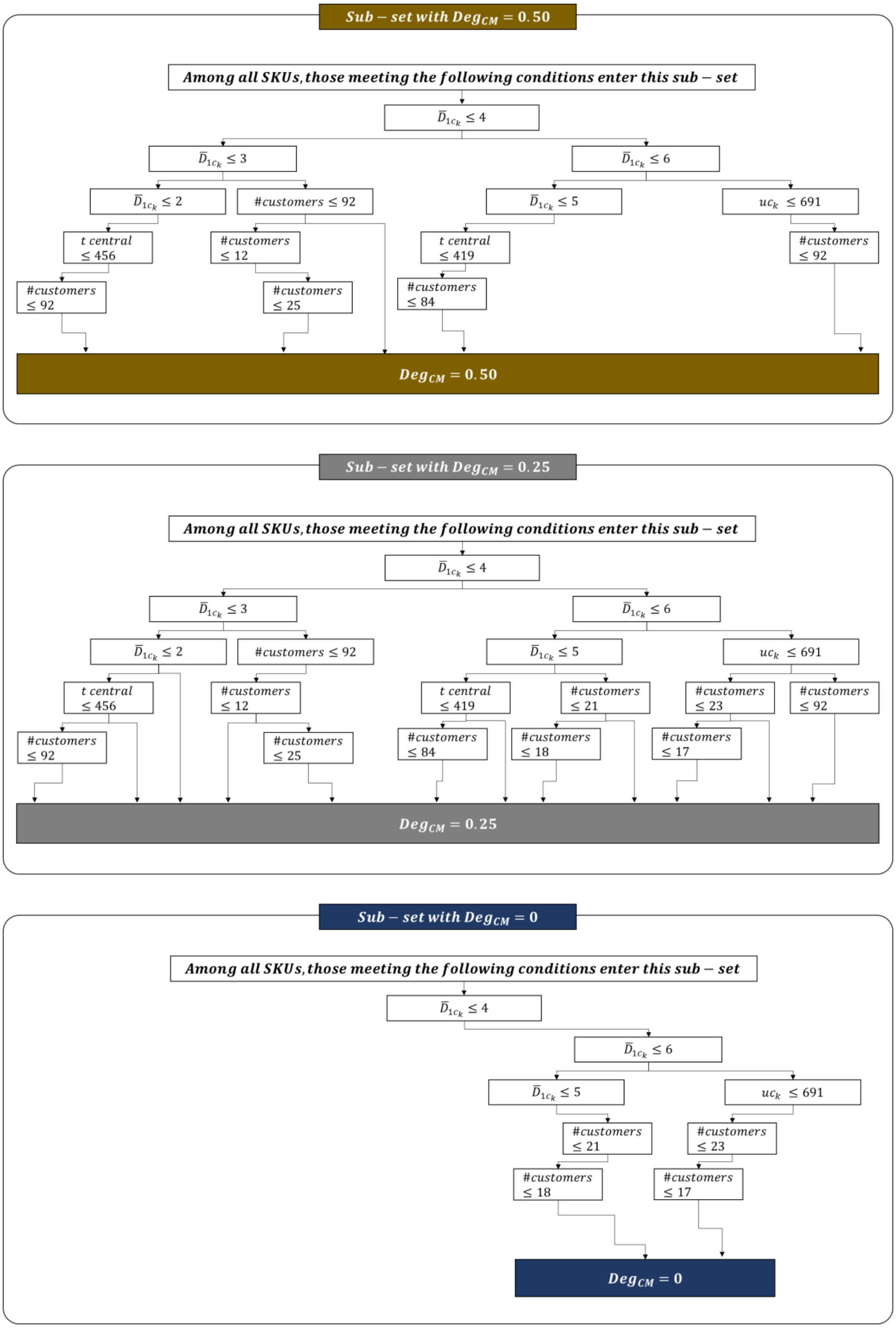

Figure 25. Conditions suggested by Cantini et al. (2022) to divide the starting CM SKUs into three sub-sets, according to their optimal stock deployment policy (Deg_{CM})

To develop the DSS, we used a methodological framework composed of three steps for each sub-set. In **Step i**, we developed a heuristic model to review the design of existing SCs, selecting the most cost-effective alternative among those reported in Figure 24. In the heuristic model, the general problem is split into small sub-problems, nested iterative loops are built, and a specific subproblem is solved to optimality in each iterative loop. Specifically, after preliminary initialisation, the proposed heuristic model is based on three nested iterative loops: an inner loop, an intermediate loop, and an outer loop.

In the initialisation, considering the selected sub-set, its SKUs are associated with the same stock deployment policy (Deg_{CM}). Therefore, Deg_{CM} is fixed, and the number of DCs in which SKUs should be stored if they were purchased as CM spare parts is calculated (Equation 40).

$$\#DC_{CM} = \begin{cases} [(1 - Deg_{CM}) * \#customers]^{+} & if\ Deg_{CM} < 1\ and\ j = CM \\ 1 & if\ Deg_{CM} = 1\ and\ j = CM \end{cases} \tag{40}$$

Next, to compare the purchase of CM spare parts with AM production, a certain value of Deg_{AM} is chosen and fixed (selecting one of the values allowed in Figure 20). Then, the number of DCs in which SKUs should be stored if they were produced in AM is calculated (Equation 41).

$$\#DC_{AM} = \begin{cases} [(1 - Deg_{AM}) * \#customers]^{+} & if\ Deg_{AM} < 1 \\ 1 & if\ Deg_{AM} = 1 \end{cases} \tag{41}$$

At this point, the focus is put on a single DC, where the three nested iterative loops are performed, considering as initial values $\#3DP_d = 1$ and $F_d = K$. Specifically, the inner loop selects the optimal manufacturing technology (CM or AM) for all SKUs in the considered sub-set. Next, the intermediate loop determines the number of 3D printers required to meet the production of AM spare parts. Finally, the outer loop suggests optimal stock deployment policies, completing the SC design review. Figure 26 schematically represents how to apply nested iterative loops. See Paper 4 for a more detailed explanation of the heuristic model and its constituting equations.

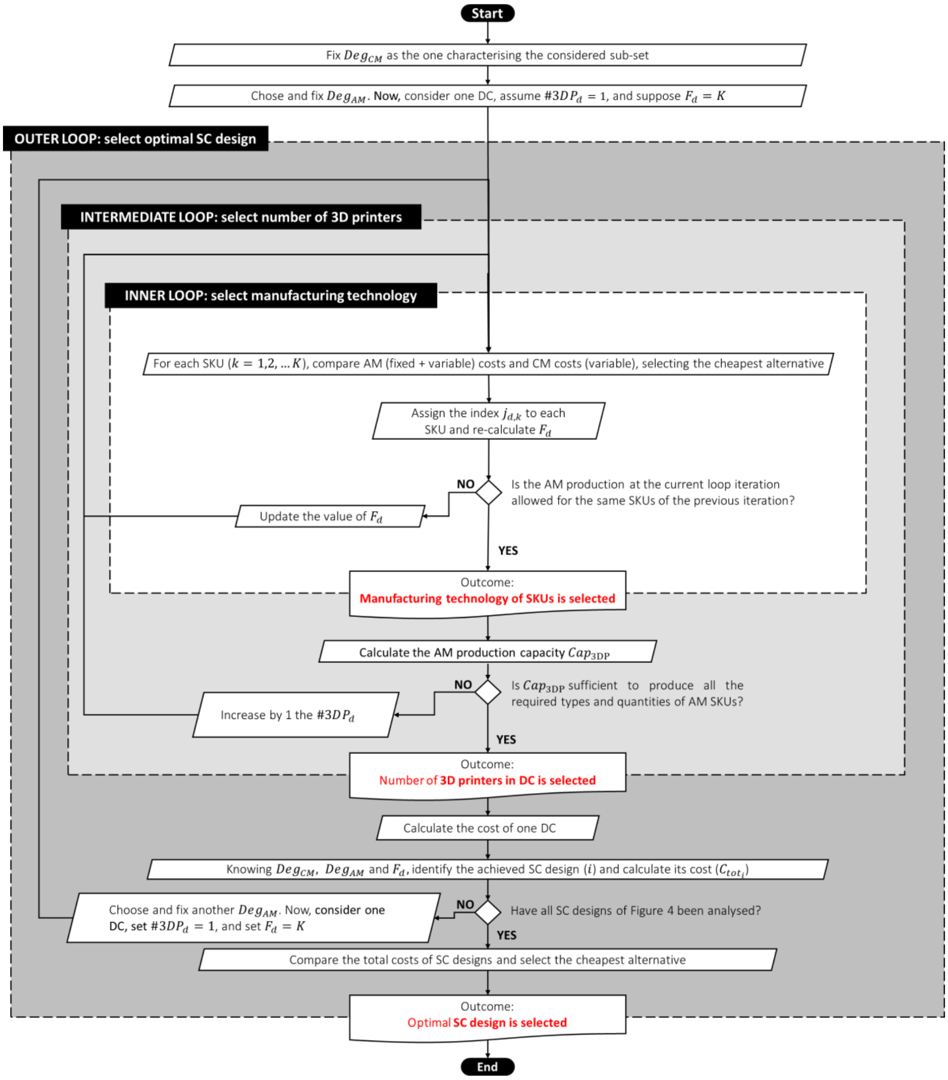

Figure 26. Schematic representation of the heuristic model

After developing the heuristic model, **Steps ii-iii** leveraged the experimental research was leveraged as follows. In ***Step ii***, we performed a parametric analysis for each sub-set to investigate a sample of 1,000,000 realistic SC scenarios (i.e., case studies of spare parts SCs with different numbers of customers and SKUs, where each SKU is characterised by different demand, purchasing costs, transportation costs, backorder costs, required service level, etc.). The SC scenarios were collected by associating the input parameters of the heuristic model with Sobol quasi-random values (following the procedure explained in Section 3.1.4), according to the admissible ranges listed in Table 9. Then, each SC scenario was submitted to the heuristic model of Step i, and its related optimal SC configuration was determined.

Table 9. Sobol values assumed in the parametric analysis. The upper and lower limits of each range were updated based on the considered sub-set. Input parameters not listed in this table were assumed to be fixed (see Paper 4)

Input parameter	Range of admissible values	Unit measure	Source used to define the ranges
$\#customers$	integers between 5 and 100	-	(Cantini et al., 2022)
SL	floats between 0.85 and 0.99	-	(Cantini et al., 2022)
$\overline{D}_{1c_k}$	integers between 1 and 7	units/year	(Knofius et al., 2021)
$t\ central$	floats between 100 and 2,000	€/transportation	(Cantini et al., 2022)
c_{b_k}	floats between 1,000 and 100,000	€/backorder	(Peron et al., 2021)
L_k	integers between 4 and 26	weeks	(Knofius et al., 2021)
K	integers between 10 and 5,000	-	Authors' choice
n_k	floats between 1 and 3	-	(Knofius et al., 2021)
uc_k	floats between 10 and 2,500	€/unit	(Knofius et al., 2021)

Finally, in ***Step iii***, we obtained the desired DSS (one per sub-set) by feeding and training a decision tree algorithm with the results of the Sobol-based parametric analysis (as explained in Section 3.1.4). Figure 27 depicts the DSS related to the sub-set with $Deg_{CM} = 0$ (the other DSSs are provided in Paper 4). The DSS was pruned (see Paper 4), searching for a trade-off between accuracy ($A = 86.5\%$, Equation 2) and user-friendliness (few questions to be answered to get a solution). Finally, we evaluated the performance of the achieved DSS with proper KPIs (Equations 3-5), which are reported in Figure 27.

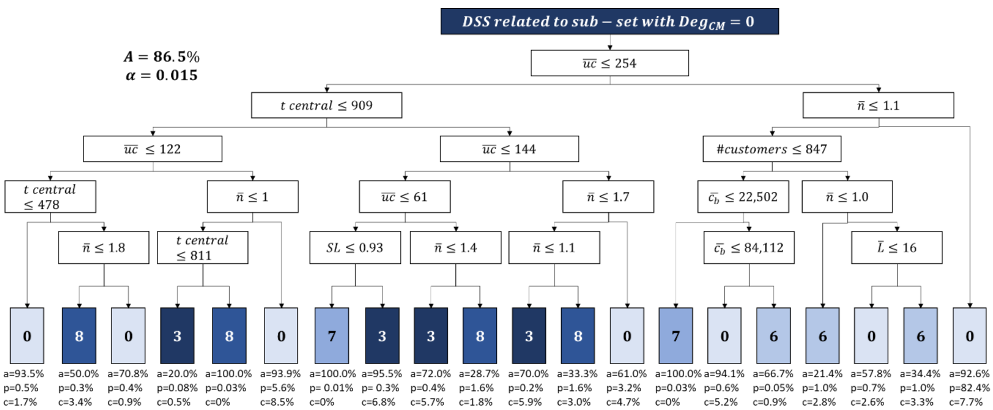

Figure 27. DSS related to sub-set with $Deg_{CM} = 0$. The numbers inside each leaf refer to Figure 24

To conclude this sub-section, we achieved a DSS (one per sub-set), which suggests an optimal (cost-effective) SC configuration among those listed in Figure 24, optimising the following aspects simultaneously:

- the stock deployment policies of individual SKUs, opting for centralisation ($Deg = 1$), decentralisation ($Deg = 0$), or hybrid stock deployment policies ($Deg = 0.25; 0.50;\ 0.75$);
- the manufacturing option of each SKU, indicating whether to purchase CM spare parts or produce in-house AM items, and suggesting when to adopt single- or dual-sourcing.

The main findings of this study can be summarised as follows: the DSS provided for each sub-set is robust since a decision tree with accurate leaves is achieved, or, at least, the DSS forecasts prevent spare parts retailers from paying a high percentage of cost increase (according to Equation 5, c is always less than 10%, often below 5%) in the case of wrong predictions. Moreover, the DSS related to each sub-set proves that, despite the advantages of risk-pooling, the centralisation of spare parts (in SCs with Deg_{CM} or Deg_{AM} higher than 0.75) is rarely advantageous and is never suggested as cost-effective. Conversely, decentralised and hybrid SCs are often convenient, especially with Deg_{CM} or $Deg_{AM} \leq 0.25$. Finally, the input parameter $\#customers$ has a low impact on the decision-making process and did not appear in any DSS.

The DSS (one per sub-set) is the main outcome of this subsection, answering both RQ2 and RQ3. However, this work makes the following two additional contributions: (i) a heuristic model (Figure 26) that to quantitatively compares SC configurations with different stock deployment policies and compares the purchase of CM spare parts with AM in-house production; (ii) the results of the DSSs have quantitatively demonstrated that, in the case of spare parts SCs, inventory decentralisation or hybrid stock deployment policies with a low degree of centralisation ($Deg = 0.25$) are usually cost-effective, while other stock deployment policies (tending towards inventory centralisation) are convenient only in rare cases.

4.4. General discussion of the results

This section delves into the meaning and relevance of the results achieved in this project.

Reviewing the configuration of spare parts SCs is fundamental for the success of spare parts retailers. However, this is not an easy task, and optimising stock deployment policies can be particularly problematic, as confirmed by both real companies (which prompted the development of this study) and recent studies (Basto et al., 2019; Eldem et al., 2022). No comprehensive literature review has been provided to summarise the existing research in this field. Few quantitative methodologies have been provided by the literature to identify the optimal alternative between inventory centralisation, decentralisation, and hybrid stock deployment policies for each SKU. Finally, this optimisation problem is further complicated by the possibility of producing spare parts with two manufacturing technologies (AM and CM), which affect the characteristics of SCs, but without being able to quantify their impacts. Against this backdrop, we believe that the results of this research project can be useful for both researchers and spare parts retailers, since an answer to the following research questions was provided: **(RQ1)** What are the extant literature and driving research streams on the topic of stock deployment in spare parts SCs? **(RQ2)** What viable heuristic methodologies can spare parts retailers use to review their stock deployment policies? **(RQ3)** What is the optimal manufacturing technology for spare parts in SCs with different stock deployment policies?

To answer RQ1, this study was the first to carry out an SLNA to determine the existing studies and driving research streams on the topic of stock deployment in spare parts SCs. The results of the SLNA strongly mattered because they provided an overview of the current body of knowledge, confirming the aforementioned literature gap and spare parts retailers' difficulties (thus underlining the need to deepen this research field). The lack of a previous literature review on the topic of stock deployment in spare parts SCs was a clue about the scarce interest of researchers in this field, contrasting with the urgent request received from two real companies to address this problem. In addition, although different stock deployment policies were mentioned for the first time almost 100 years ago (Taylor, 1931), the SLNA pointed out that, against expectations, only 170 papers were published on this topic, most of which were published in the last 10 years, resulting in qualitative discussions, as confirmed by several authors (Mangiaracina et al., 2015; Milewski, 2020). Given the need to deepen this research field, another relevant result of the SLNA was that it enabled us to envision future research opportunities. Five main themes and three driving research streams emerged, which constituted a solid basis on which to build new knowledge about the optimisation of stock deployment policies and the review of spare parts SC configuration. By combining the results of the SLNA with the specific requests for support received from two real companies, this project identified two driving research streams of primary importance to investigate to fill the literature gaps and alleviate spare parts retailers' difficulties: (i) the optimisation of stock deployment in SCs with AM spare parts; and (ii) the development of heuristic optimisation methodologies (instead of exact optimisations or simulations) to review the stock deployment policies in spare parts SCs. These results can be considered interesting based on the following considerations. Regarding the need to optimise stock deployment in AM spare parts SCs, the findings confirms that both researchers and spare parts retailers believe AM is a strategic opportunity to improve SC performance, replacing CM or complementing its potentialities, although the literature in this field is not yet sufficiently thorough (Xu et al., 2021). Regarding the need to develop structured heuristic methodologies, this result contrasts with the trends in the literature, where only few quantitative studies have been proposed to optimise stock deployment policies in spare parts SCs (Costantino et al., 2013; Daskin et al., 2002; Sherbrooke, 1968). However, researchers and spare parts retailers both argue that heuristic optimisation methodologies are needed, being preferable over exact optimisation methodologies or simulations since, although they accept approximate solutions (achieving local optimums, and not necessarily the absolute ones), they can usually be applied in real companies, and where quite often advanced technologies and computational resources are missing, and quick and easy-to-use methodologies are needed. The lack of quick and easy-to-use heuristic methodologies explains why, despite the well-known importance of optimising stock deployment policies and reviewing the configuration of spare parts SCs, many spare parts retailers still choose a starting SC configuration and never question it over time, thus limiting their performance (Hu et al., 2018).

Besides the SLNA, the other outcomes of this research project are three heuristic methodologies and two quick and easy-to-use DSSs, which support spare parts retailers in comparing different stock deployment policies and different spare parts manufacturing options (enabling an adequate SC configuration review). Going into more detail on each outcome, the following reflections on the achieved results can be offered. As the first outcome, we proposed a data-driven heuristic methodology ("SP-LACE") to review the configuration of spare parts SCs by optimising not only the stock deployment policies (which are the primary focus of this study) but also the supply ones. SP-LACE is composed of two stages. Stage 1 is based on a multicriteria ABC criticality classification of spare parts, which suggests how to associate individual SKUs with optimal stock deployment and supply policies. Stage 2 then uses an analytical model to evaluate the economic benefits obtained by reviewing the SC configuration (instead of keeping it unchanged over time). The developed methodology was tested and validated on two real case studies, leading to the following results. First, SP-LACE is a structured, effective, quick, and easy-to-use methodology for reviewing the configuration of spare parts SCs. Second, SP-LACE reduces SC costs while guaranteeing high service levels and improving the performance of spare parts SCs. Finally, SP-LACE is the first literature methodology capable of quantitatively demonstrating the importance of reviewing the configuration of spare parts SCs. So, what do these results tell us? Why are they relevant? First, applying SP-LACE in two real companies allowed us to demonstrate that the theoretical discussions on the importance of reviewing spare parts SC configurations find strong reflection in practice. For the first time in the literature, SP-LACE allowed us to quantitatively demonstrate that reviewing the SC configuration by adopting structured methodologies improves the SC performance. Conversely, keeping the starting SC configuration unchanged over time implies achieving unnecessary SC costs, as well as high inventory levels, number of supply orders, and backorders. Furthermore, although we might think that reviewing the configuration of an existing SC is a burdensome process that is difficult to repeat over time, SP-LACE made it possible to demonstrate its practical feasibility in two real companies. In particular, in one case study, SP-LACE was applied twice, proving that a real company was able to update its stock deployment (and supply) policies and review the SC configuration on an annual basis. Moreover, although we might think that the ABC criticality classification of spare parts is an obsolete technique (superseded by more advanced optimisation methodologies), SP-LACE brought new life to it. In fact, SP-LACE showed that the ABC criticality classification can be used not only to manage spare parts stocks in a single DC (which is the application usually proposed in the literature) but also to optimise stock deployment policies in multiple DCs. Therefore, the results of SP-LACE were useful to show that although ABC criticality classification is a well-known simple heuristic technique, it is still highly appreciated by companies, provides valuable results, and is not sufficiently explored in the literature.

SP-LACE represented the first heuristic methodology proposed in this thesis, but it did not address the problem of selecting the optimal spare parts manufacturing technology to compare the impacts of AM and CM on spare parts SCs. When developing SP-LACE, we focused solely on answering RQ2. Therefore, after developing SP-LACE, aiming to answer both RQ2 and RQ3, we proposed two DSSs (achieved in the form of decision trees after developing two heuristic methodologies). The two DSSs guide spare parts retailers in reviewing the SC configuration by answering a few sequential questions and optimising both the stock deployment policies and manufacturing technologies of individual SKUs. Both DSSs were achieved by exploiting mathematical modelling and experimental research, comparing the SC costs achieved by adopting different combinations of stock deployment policies and manufacturing options, and selecting the most cost-effective one. The two DSSs are complementary. The first is used to select the most cost-effective combination of stock deployment policies and manufacturing options in SCs, where both AM and CM spare parts are purchased from suppliers. Instead, the second DSS evaluates the most cost-effective combination of stock deployment policies and manufacturing options in SCs where CM spare parts are purchased from suppliers and AM spare parts are produced in-house (inside DCs). So, why are the two DSSs (and the heuristic methodologies used to achieve them) relevant, and what do they tell us? First, the two DSSs (and the heuristic methodologies) represent the first literature attempt to evaluate the impacts of different manufacturing technologies on spare parts SCs, selecting the optimal one for spare parts. Hence, their results show, for the first time, the optimal spare parts manufacturing technology to be adopted and how different manufacturing technologies change the selection of optimal stock deployment policies, representing a non-negligible variable to be considered in this decision-making process. Second, the two DSSs promoted our understanding of which input parameters mainly impact the SC configuration review and what can be neglected instead. For example, the DSS in Section 4.3.1 showed that two parameters (procurement lead time and expected service level) have a negligible impact on the investigated decision-making process. Therefore, the DSSs reduced the SC configuration review to a quick and easy-to-use process, minimising the evaluation efforts to answering only a few questions (driven by the value of input parameters with non-negligible impact). Third, as stated by Westerweel et al. (2018), the majority of spare parts retailers currently manage CM spare parts but are interested in evaluating a switchover to AM ones. Therefore, the two DSSs constitute relevant literature results, since they represent the first tools capable of evaluating the convenience of performing the aforementioned switchover, suggesting investments in AM technologies only if they are economically profitable. Finally, the DSSs' results, for the first time in the literature, suggest spare parts retailers preferring inventory decentralisation or hybrid stock deployment policies with a low degree of centralisation ($Deg_i = 0.25$), showing that tending towards centralisation is profitable only in rare cases.

To conclude, an important result that unites all the provided heuristic methodologies and DSSs is that they have been developed to be quick, easy-to-use, and accessible to all companies. Therefore, we hope that this research project will pave the way for encouraging spare parts retailers to regularly review their SC configuration, improve their SC performance, and adequately spread the use of AM technologies in the field of aftersales (thus enhancing an industrial revolution).

However, even with the relevance of the presented results, the current research study suffers from some limitations (which will be described in Section 5.4) and represents only a starting point for a prosperous future of research. Therefore, we hope that this research project can inspire other researchers to continue investigating the topic of reviewing the configuration of spare parts SCs, considering different stock deployment policies and manufacturing options.

5. Conclusions

This section provides summarises the findings and the theoretical and practical contributions provided by this research study and provides some concluding remarks. Moreover, the research limitations are discussed, and some recommendations for future research are proposed.

5.1. Summary

The objective of the current research project was to support and create new knowledge for researchers and practitioners (spare parts retailers) on how to review the configuration of spare parts SCs, focusing on optimising stock deployment policies and considering different manufacturing options. In addition, a more general aim was to propose future research opportunities related to the considered research areas, thus inspiring new researchers to continue investigating this topic. To reach these goals and develop richer and more thorough knowledge of the research area, this study adopted a mixed-methods approach, leveraging a combination of the following research methods:

1. An SLNA provided in-depth knowledge about the extant literature on the topic of stock deployment in spare parts SCs and underlined the driving research streams, which inspired possible future research opportunities and new research questions for this study.
2. Mathematical modelling was used to conceive and develop novel heuristic methodologies to guide the rules for reviewing stock deployment policies (and the consequent SC configuration) in spare parts SCs with different manufacturing options.
3. Case study research accomplished several tasks. First, consulting two real companies enabled us to formulate the problem to investigate in this research and facilitated testing and validating one of the proposed heuristic methodologies by applying it to the two case studies. Second, the collaboration with two real companies allowed us to verify whether the proposed methodologies and their simplifying assumptions were considered realistic not only by the scientific community but also by industrials with decades of experience in the field of spare parts retail.
4. Experimental research allowed the use of sampling strategies to develop many realistic case studies, testing them to attain parametric analyses. Experimental research allowed us to generalise the results of the parametric analyses by leveraging machine learning algorithms. Therefore, quick and easy-to-use DSSs were achieved in the form of decision trees, tasked with supporting spare parts retailers in reviewing the SC configuration by selecting not only the optimal stock deployment policy but also the spare parts manufacturing option.

By leveraging these research methods, the present research project made the following contributions by answering three research questions.

RQ1: What are the extant literature and driving research streams on the topic of stock deployment in spare parts SCs?

The findings of Paper 1 and the SLNA revealed the extant literature on the topic of stock deployment in spare parts SCs and identified five main research themes through which the literature in this field could be clustered. Among the five themes, two were recognised as driving research streams: (i) the optimisation of spare parts deployment in closed loop SCs; and (ii) and the optimisation of stock deployment in SCs with AM spare parts. An additional driving research stream was underlined regarding the specific methodology used for optimising stock deployment: (iii) the use of heuristic optimisation (instead of exact optimisation or simulation). Knowledge of these driving research streams is of considerable importance in inspiring new research opportunities and laying the foundations for deriving future research activities.

Given the initial motivations behind this work, and due to time restrictions, only two out of three driving research streams (ii and iii) were selected for the rest of this project. This project originated from the request for support received by two companies that needed quick and easy-to-use methodologies to review stock deployment policies in spare parts SCs and more indications on how to introduce AM technologies in their companies. Since Paper 1 confirmed the interest of both industrial researchers and practitioners in further investigating research streams (ii) and (iii), we focused our attention on those and derived two additional research questions.

RQ2: What viable heuristic methodologies can be proposed to review stock deployment policies in spare parts SCs?

The findings of Papers 2-4 provided spare parts retailers with three heuristic methodologies with which to review stock deployment policies in spare parts SCs. Three different methodologies were proposed since they allow spare parts retailers to approach the problem from three different perspectives. The first methodology is based on a multicriteria ABC criticality classification of spare parts and the development of two procedural stages, which were defined and validated through mathematical modelling and case study research. This first methodology allows achieving two results: associating optimal stock deployment policies (as well as optimal supply policies) with individual SKUs and evaluating the economic benefits of the reviewed SC configuration. This heuristic methodology was tested on two different case studies, leading to successful results (in terms of SC costs, time consumption, and reliability of its results), and demonstrating, for the first time in the literature, the importance of regularly reviewing the configuration of spare parts SCs. However, such a methodology does not provide explicit indications of how to match optimal stock deployment policies with optimal spare parts manufacturing options (AM or CM). Therefore, by means of mathematical modelling and experimental research, a second and third heuristic methodologies were provided, which implied defining two mathematical models, performing two parametric analyses, and training two respective machine learning algorithms. The second and third heuristic methodologies were finalised by the development of two complementary DSSs, which allowed us to deal with the following issues. The second heuristic methodology (with its respective DSS) compares the cost-effectiveness of different stock deployment policies in SCs where stocks of both AM and CM spare parts are assumed to be purchased from suppliers (in the form of finished products). The third heuristic methodology (with its respective DSS) compares the cost-effectiveness of different stock deployment policies in SCs, where stocks of CM spare parts are assumed to be purchased from suppliers, while stocks of AM spare parts are assumed to be produced in-house (by installing 3D printers inside DCs).

RQ3: What is the optimal manufacturing technology for spare parts in SCs with different stock deployment policies?

The findings of Papers 3 and 4 answered both RQ2 and RQ3. In fact, the heuristic methodologies proposed in the respective papers enabled the development of two DSSs, which supported spare parts retailers in making two decisions at the same time: how to review the stock deployment policy in spare parts SCs and how to choose the optimal manufacturing option between AM and CM spare parts (evaluating different sourcing options, including the purchase or in-house production of stocks). The proposed DSSs (represented by decision trees) proved to be quick and easy-to-use, providing spare parts retailers with optimal indications by answering only a few questions. Moreover, they suggested robust solutions being characterised by accurate decision tree leaves or, at least, by leaves that, in case of a wrong prediction, do not negatively impact the companies' economies (implying an SC total cost similar to that of the correct prediction, thus leading to an average percentage of cost increase less than 10%, and often below 5%).

5.2. Theoretical contributions

The current research study has several contributions to theory, which are summarised in the main outcomes reported in Table 10.

Table 10. Contributions to theory: main outcomes

Main outcomes	Papers			
	1	2	3	4
Extant literature on stock deployment policies in spare parts SCs	x			
Driving research streams related to the topic of stock deployment in spare parts SCs	x			
Proposal of a data-driven heuristic methodology (based on a multicriteria ABC criticality classification) that can be used to review stock deployment policies in SCs with CM spare parts		x		
Proposal of a DSS (developed through a heuristic methodology) to review the SC configuration by optimising the stock deployment policies and choosing the optimal alternative between the purchase of AM or CM spare parts			x	
Proposal of a DSS (developed through a heuristic methodology) to review the SC configuration by optimising the stock deployment policies and choosing the optimal alternative between the purchase of CM spare parts and the in-house production of the AM ones.				x

The first and second theoretical contributions of this project come from the findings of the SLNA. First, by conducting the SLNA, we defined and reorganised the extant body of knowledge on the topic of stock deployment in spare parts SC. We then identified three driving research streams that are useful for inspiring future research opportunities, allowing researchers to open new research areas and questions on the investigated topic. For instance, in this project, two of the driving research streams were used to derive two research questions (RQ2 and RQ3), which were then answered to create new knowledge.

The third contribution relates to the proposal of a novel data-driven heuristic methodology that can be used to review the configuration of spare parts SCs, optimising both the stock deployment policies (which are the main focus of this study) and the stock supply policies. Since the existing literature overlooks the problem of reviewing the configuration of spare parts SCs, the proposed methodology represents an attempt to fill this literature gap. Moreover, the proposed methodology is the first one in the literature to quantitatively demonstrate the importance of reviewing the configuration of spare parts SCs, proving the importance of exploring this research topic.

The fourth and fifth contributions relate to the proposal of two complementary DSSs (developed through two heuristic methodologies), which can be used to review the configuration of spare parts

SCs, optimising both the stock deployment policies and the spare parts manufacturing options in two different types of SC. The first DSS compares SCs, where AM and CM spare parts are purchased from suppliers, and the second DSS evaluates SCs, where CM spare parts are purchased from suppliers and AM spare parts are produced in-house. The proposed DSSs (together with the heuristic methodologies used to achieve them) represent the first effort in the literature to quantitatively compare the performance of SCs with AM and CM spare parts, enabling the selection of the optimal manufacturing option. In addition, the proposed DSSs are the first solutions provided by the literature to optimise the stock deployment policies and manufacturing options in spare parts SCs at the same time. Moreover, consulting the proposed DSSs can help identify the independent parameters that affect the performance of different SC configurations and understand the extent to which these parameters impact the selection of stock deployment policies and manufacturing options. As a complement, the DSSs also highlight which parameters have a negligible effect on the decision-making process. Finally, the proposed DSSs can be used (together with the aforementioned data-driven heuristic methodology) to demonstrate the importance of reviewing the spare parts SC configuration and achieving benefits in terms of SC costs and service levels.

To conclude, one final theoretical contribution can be underlined, which is common to all the research activities conducted in this project. All the developed studies had a common goal: to investigate the optimisation of stock deployment policies in spare parts SCs. As this concept is disregarded by the literature (there is a lack of clear indications on how to compare scenarios of centralisation, decentralisation, and hybrid stock deployment policies), all the outcomes of this project can be considered a useful contribution to fill this literature gap, providing new knowledge on an overlooked topic.

5.3. Implications for practice

Since this research project was initially motivated by the requests of two real companies, all the achieved outcomes of Table 10 led to both theoretical contributions and strong implications for practice.

First, both the considerations extracted by the literature and the results achieved by developing and applying novel heuristic methodologies and DSSs were useful in showing spare parts retailers the importance of reviewing the configuration of spare parts SCs. Many spare parts retailers currently choose the SC configuration only once (when the business is founded) and never question it. However, in this project, the following result was demonstrated: regularly reviewing the configuration of spare parts SCs is the only way for spare parts retailers to maintain a successful position in the market. By reviewing the configuration of spare parts SCs, the alignment of spare parts logistic activities with customer needs is guaranteed, despite unpredictable demand fluctuations. As a result, SC costs are minimised, and high service levels and customer satisfaction are achieved.

Before this research project, the existing literature overlooked the problem of reviewing the configuration of spare parts SCs. Therefore, we hope that the findings of this research will encourage spare parts retailers to start reviewing the configuration of existing spare parts SCs. To achieve this goal, different heuristic methodologies and DSSs were intentionally developed and proposed in this project to support spare parts retailers in reviewing the configuration of spare parts SC, focusing on optimising stock deployment policies and spare parts manufacturing options. The proposed heuristic methodologies and DSSs were proven to suggest cost-effective solutions that produce benefits in terms of average inventory levels, the number of supply orders to replenish DCs, the number of backorders, service levels, and SC costs.

Specifically, spare parts retailers were provided with practical solutions applicable in real companies (also with thousands of SKUs and few advanced technologies and computational resources). We developed quick and easy-to-use heuristic methodologies and DSSs that rely on the input data and information commonly available in company databases.

As an additional practical implication, the proposed heuristic methodologies and DSSs suggest which independent input parameters spare parts retailers should consider, the procedural steps to perform, and the questions to answer when aiming to review and optimise the configuration of spare parts SCs.

Finally, the equations and the findings of the proposed heuristic methodologies and DSSs show how each independent input parameter affects SC performance. Therefore, the input parameters with major impacts on the performance of SC configurations are highlighted, enabling spare parts retailers to focus on their optimisation.

5.4. Research limitations

No research is conducted without limitations. This subsection highlights the main limitations of this research project.

First, because of time constraints, not all the research opportunities related to the optimisation of stock deployment policies and the review of spare parts SC configurations have been investigated. The developed SLNA identified five main themes and three driving research streams related to the topic under investigation. From the three driving research streams, new research opportunities were identified that concerned: the optimisation of stock deployment policies in closed loop spare parts SCs or SCs with AM spare parts, and the use of heuristic optimisation methodologies to optimise stock deployment policies in spare parts SCs. In addition, for each driving research stream, many research questions could be derived, generating, in turn, other research opportunities. However, a longer period would be necessary to study all the driving research streams and their related research opportunities, while the current research had only a three-year period. For this reason, in this study, we focused only on two (out of three) driving research streams (stock deployment of AM spare parts, and the use of heuristic optimisation methodologies), exploring only one research question for each driving research stream.

Second, we provided spare parts retailers with heuristic methodologies to optimise stock deployment policies in spare parts SCs and, consequently, to review the SC configuration. However, these methodologies rely on simplifying assumptions, which limits the generalisation of the achieved results. Moreover, like all heuristic methodologies, they may lead to approximate solutions that represent a local (not an absolute) optimum.

Third, we built the proposed DSSs by adopting decision tree algorithms. This particular type of algorithm was selected because of its quickness and user-friendliness. However, other more sophisticated and accurate algorithms, such as Random Forests, could have been selected among the machine learning algorithms. In addition, regarding the DSSs, their practical application in real companies could be analysed not to explain how to use the DSSs (which has already been done in Papers 3-4), but rather to investigate how the SC performance changes after reviewing the SC, further confirming the DSS effectiveness.

Finally, in addition to the main limitations mentioned above, it is necessary to highlight that each study in the appended publications has its own specific limitations, which are provided in the conclusion sections of Papers 1-4.

5.5. Future research developments

In this section, we report possible future research developments for the present research project.

First, further investigations could be developed to examine how to review the configuration of spare parts SCs by optimising stock deployment policies and considering different manufacturing options. Specifically, since not all of the driving research streams underlined in Paper 1 were explored in this study, they could be investigated in future works. For example, studies could be conducted on how to optimise stock deployment policies in closed loop spare parts SCs, which were not considered here. Moreover, since only one research question was derived from each of the considered driving research streams, additional research questions could be identified to develop new studies.

Second, step by step, the simplifying assumptions behind the proposed heuristic methodologies and DSSs could be removed or relaxed to achieve more general results and increase the application range of the proposed solutions.

Third, since only heuristic methodologies were provided, researchers could try to compare them with exact optimisation or simulation methodologies to check their effectiveness, quickness, and user-friendliness, thus confirming the convenience of using heuristics. Moreover, the proposed heuristic methodologies and DSSs (particularly DSSs) could be applied in other case studies to replicate their application and confirm the benefits that are achievable by reviewing the spare parts SC configuration.

Fourth, all the provided heuristic methodologies could be applied to a common case study to compare their performance and underline their commonalities and differences. This research activity could also be useful for supporting spare parts retailers in confirming under which conditions a specific methodology should be preferred with respect to others.

Finally, each of the appended publications reports specific future research opportunities to improve the proposed works. Therefore, if interested, we refer the reader to the conclusion sections of Papers 1-4 to obtain additional knowledge on the considered topic.

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Part II: Collection of papers

Paper 1: Cantini, A., Ferraro S., Leoni L., and Tucci M., 2022. Inventory centralization and decentralization in spare parts supply chain configuration: a bibliometric review. Proceedings of the Summer School Francesco Turco.

Paper 2: Cantini, A., Peron, M., De Carlo, F., and Sgarbossa, F., 2022. A data-driven methodology for the dynamic review of spare parts supply chain configuration. International Journal of Production Research (currently under review).
This paper originates as an extended version of the paper "Cantini, A., De Carlo, F., Leoni, L., Tucci, M., 2021. A novel approach for spare parts dynamic deployment", which has been ***published*** *at the "Proceedings of the Summer School Francesco Turco" and* ***awarded with the "Best Paper Award"****. However, the awarded paper (original short version) is not appended to this thesis since its content is entirely included and properly extended in the above paper (extended version). Therefore, the authors consider redundant its consultation.*

Paper 3: Cantini, A., Peron, M., De Carlo, F., Sgarbossa, F., 2022. A decision support system for configuring spare parts supply chains considering different manufacturing technologies. International Journal of Production Research 0, 1-21. doi: 10.1080/00207543.2022.2041757.

Paper 4: Cantini, A., Peron, M., De Carlo, F., and Sgarbossa, F., 2022. On the impact of additive manufacturing on the review of spare parts supply chains configuration: a decision support system. International Journal of Production Research (currently under review).

Inventory centralization and decentralization in spare parts supply chain configuration: a bibliometric review

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Abstract: In recent decades, the scientific literature has underlined the difficulties in configuring spare parts Supply Chains (SCs) due to the need of minimizing inventory stocks, while facing demand unpredictability and ensuring high service levels. When dealing with spare parts retail companies, it is essential to establish the optimal SC configuration. Indeed, aligning spare parts storage and distribution activities with customer needs ensures customer satisfaction, increased sales profits, and efficient company performance. Configuring spare parts SCs implies performing two tasks. First, defining the deployment strategies of spare parts into Distribution Centers (DCs), choosing between antithetical solutions such as centralization or decentralization. Then, establishing inventory control policies for each item in each DC, planning how many stocks to supply and how often. Regarding the task of establishing the spare parts supply, several contributions have been provided by the literature, proposing methods and tools to control inventories in a single DC. Conversely, against expectations, the literature overlooks the task of planning the spare parts deployment. Indeed, although the different characteristics of centralized or decentralized SCs are known since the 1960s, a few studies have been provided to support spare parts retailers in choosing between centralization and decentralization. In this context, the present paper offers a bibliometric review carried out with a Systematic Literature Network Analysis (SLNA) on the topic of spare parts deployment in SC configuration and the choice between centralization and decentralization. The proposed bibliometric review is useful to understand the state of the art in the analyzed domain, also identifying the top contributing research studies. As a result, descriptive metrics on the retrieved papers are provided to give an overview of the current body of knowledge and lay the foundations for defining possible gaps and future research activities.

Keywords: spare parts logistics, supply chain configuration, inventory allocation, inventory pooling, literature review.

I. INTRODUCTION

Spare parts are strategic assets to ensure the proper execution of maintenance activities in industrial plants. Indeed, they allow restoring the functioning of production equipment by replacing damaged components [1]. Given the significant role of spare parts, the scientific literature [2] has emphasized how crucial it is for spare parts retailers to ensure efficient supply chains (SCs), where the right spare parts are stored and distributed in the right place (close to the damaged components) at the right time (breakdown time [3]). In fact, efficient SCs enable spare parts retailers to optimize business performance by avoiding inventory stock-outs and delivering high service levels, while minimizing purchasing, storage, and distribution costs and efforts [4]. Moreover, efficient spare parts SCs trigger customer satisfaction by providing them with the Stock Keeping Units (SKUs) necessary for maintenance activities, thus minimizing unexpected equipment downtimes and the related financial and operational negative effects [5]. In this context, one of the actions that spare parts retailers can take to achieve efficient SCs is to optimally configure their SCs [6]. An optimal configuration of spare parts SCs enables companies to align logistics activities with customer demand, thus achieving higher performance and competitive advantage. Indeed, a well-configured SC allows a customer-oriented after-sales service, which encourages customers' loyalty, repurchase intentions, and market share [7]. However, the optimal configuration of spare parts SCs is hampered by specific features that distinguish spare parts from other items (commodities, raw materials, or productive supplies) [8]. Among these features, Huiskonen [9] mentioned the unpredictable demand, the prices of individual parts which can be very high, the high number of SKUs that spare parts retailers usually manage, and, finally, the expected customer service level which is typically very high. In addition to this, pursuing conflicting goals such as ensuring high service levels while minimizing inventory costs, another difficulty is faced when configuring spare parts SCs: choosing between SC configurations characterized by different degrees of inventory pooling (which are associated with antithetical benefits). Specifically, two opposite SC configurations can be selected (namely, centralization and decentralization) as well as any hybrid configuration that is a trade-off between the two above stated [10]. In centralization, the maximum degree of inventory pooling is achieved by storing all the SKUs in a single central distribution center (DC), which is tasked with serving all the customers. The advantages of centralization include mitigation of demand uncertainty (risk-pooling effect), minimal inventory levels, low numbers of replenishment orders, and minimal inventory costs, but implying high delivery times and reduced SC flexibility [1]. In contrast, in decentralization, the minimum degree of inventory pooling is obtained by storing SKUs in multiple independent DCs, each serving nearby customers. Decentralization has countervailing advantages to centralization, including high SC flexibility and responsiveness due to short distances between DCs and customers, low spare parts delivery times, and consequent high service levels, but implying high inventory costs, high numbers of replenishment orders, low inventory turnover, and no advantages related to economies of scale and risk-pooling [11]. Given the aforementioned difficulties, structured methodologies should be provided to support spare parts retailers in overcoming issues and configuring SCs [12]. Specifically, such methodologies should help spare parts retailers in defining two aspects of an SC configuration [6]. First (step 1 of SC configuration), the optimal deployment of spare parts in DCs should be outlined, choosing between centralization, decentralization, and hybrid deployment alternatives with intermediate degrees of inventory pooling. Next (step 2 of SC configuration), optimal inventory control policies should be established in each DC, choosing for each SKU whether to supply it on replenishment or on-demand, when to issue supply orders and how many spare parts to supply. Concerning step 2 of SC configuration, many literature reviews [13], [14] prove that numerous methodologies have already been developed to select the optimal inventory control policy, thus optimizing spare parts supply in a single DC. Conversely, some authors [15], [16] have recently stated that step 1 of SC configuration (optimal deployment of SKUs in DCs) is overlooked by the literature. Specifically, Gregersen and Hansen [6] reported that the concepts of inventory centralization and decentralization were first introduced in 1960 [17], thus making known for a long time the impacts of different deployment strategies (with different degrees of inventory pooling) on a company's economies. Despite this, it was reported [1], [9] that few methods have been offered by the literature to deal with step 1 of SC configuration, planning the deployment of items in DCs and opting for centralization, decentralization, or hybrid configurations. Moreover, to the best of the authors' knowledge, an overview of the research conducted on step 1 of SC configuration is still missing in the literature, as well as a bibliometric review on such a topic. Nevertheless, understanding the extant literature on the topic of spare parts SC configuration with a focus on step 1 of spare parts deployment and the choice between centralization and decentralization could be of great interest for two reasons. First, to reorganize the research carried out so far by identifying the main contributions and the most prolific authors, journals, and countries. Secondly, to identify current and future research trends in the analyzed topic, thus providing a solid basis on which to build new research studies. For this reason, based on a Systematic Literature Network Analysis (SLNA), this paper presents a bibliometric review on the topic of spare parts SC configuration with a focus on step 1 of planning the SKUs' deployment in DCs, choosing between inventory centralization and decentralization. The bibliometric review is conducted aiming to answer two research questions: **(RQ1)** What are the most productive and influential countries, journals, and authors and the most influential contributions in the literature on inventory centralization/decentralization and the deployment of spare parts in DCs (step 1 of SC configuration)? **(RQ2)** What are the main themes and driving research streams that mainly concur in developing the research on the topic of inventory centralization/decentralization and the deployment of spare parts in DCs? Overall, the aims of this paper are three. First, to identify the extant literature on the analyzed topic. Secondly, to explore the top-contributing countries, journals, and authors in the field (together with their main contributions) by analyzing their number of publications and citations, and also proposing a novel graphical descriptive tool. Finally, to analyze past and current research themes related to the considered topic by examining the authors' keywords and their co-occurrence. As an outcome of this study, descriptive metrics on the retrieved research documents are provided to give an overview of the current body of knowledge. The contribution of this paper is to lay the foundations for possible future research activities in the examined domain, providing researchers with results useful to identify potential literature gaps and propose further research studies. The remainder of the present paper is organized as follows: in Section 2, the general description of the materials collected through the SLNA, and the methodology followed to conduct the bibliometric review are described. In Section 3, the results of the bibliometric review are shown. Finally, in Section 4, some conclusions on the work are provided.

II. Materials and Methodology

A. Materials

The SLNA was conducted on February 28, 2022, by searching scientific contributions on the Scopus database, which is considered the best search engine in terms of scientific journal coverage [17]. Initially, contributions including (in the title, abstract, or keywords) keywords related to both spare parts and the specific step 1 of SC configuration (i.e., pooling, centralization, decentralization, deployment, location, allocation, and their synonyms or abbreviations) were investigated by means of the following search query: *TITLE-ABS-KEY("spare part*") AND (TITLE-ABS-KEY(*centrali* OR *location* OR deploy* OR pooling).* This search query yielded 770 documents. Aiming to extract all existing contributions in the analyzed domain, no filter on the papers' publishing date was inserted. Instead, subject areas not related to the topic of research were excluded (i.e., Material Science, Energy, Earth and Planetary Sciences, Social Sciences, Medicine, Physics and Astronomy, Chemical Engineering, Chemistry, Agricultural and Biological Sciences, Biochemistry

Genetics and Molecular Biology, Arts and Humanities, Neuroscience, Health Professions, Pharmacology Toxicology and Pharmaceutics, Nursing, Immunology and Microbiology, Psychology). In this way, 682 results were found. Then, only Articles and Conference Papers were filtered, achieving 621 documents. Finally, documents written in English were filtered, obtaining 551 results. The number of contributions identified may seem high, in contrast with the remarks by the literature [1], [6] on the lack of studies on step 1 of SC configuration. However, it was considered appropriate to refine the search query based on the following semantic clarification. According to Melo et al. [18], when using keywords related to the topic of inventory “location” and its synonyms or abbreviations, Scopus finds papers dealing with three issues: (i) planning the allocation of items within a single DC, for example placing the articles on the shelves of a warehouse or planning how many items to allocate in a single DC [19]; (ii) choosing the geographical site for building a new warehouse [20]; (iii) determining how to allocate SKUs in multiple DCs, that is choosing inventory centralization, decentralization, or hybrid SC configurations [21]. Moreover, other research themes emerge not related to the topic of interest (e.g., the traceability of spare parts location using blockchains, the spare parts failure location, and the allocation of spare parts redundancies in a plant). Therefore, aiming to investigate only the aspect of inventory centralization and decentralization and the deployment of spare parts in DCs (step 1 of SC configuration), many of the 551 scientific contributions were considered not pertinent to this study. However, it was not possible to change the search query, excluding not interesting topics without discarding relevant scientific contributions in the analyzed domain. For example, modifying the search query by removing keywords such as “*location*” or “deploy*” would have removed useful papers such as the one by Patriarca et al. [22], which instead propose a method for optimally deploying spare parts in the DCs of multi-echelon SCs. Therefore, it was considered more appropriate to perform a manual selection of the collected papers, consulting their title and abstract and removing the documents not concerning the topic of interest. After the manual selection, 170 documents remained (excluding 381 papers), showing a greater interest of researchers towards the topics of spare parts positioning within a single DC, the geographical location of new facilities, or other topics, rather than on planning the stocks' deployment in DCs and choosing centralization or decentralization. Fig. 1 summarizes the followed screening process based on 4 exclusion criteria (EXs). The achieved database (170 papers) was extracted and used to develop the bibliometric review.

B. *Methodology*

A bibliometric network analysis was performed to develop this study, investigating the state of the art in the selected topic. To address RQ1, analyses on the publications and citations of each reference were developed to define the most productive and influential countries, journals, and authors in the field [23]. The most productive authors, countries, and journals were defined since they contain most of the publications on the topic of interest, being the first sources to be consulted when studying spare parts SCs and the choice between centralization or decentralization. Whereas the most influential authors, countries, and journals were identified to establish the literature contributions considered most interesting by other authors in the field. Moreover, the authors’ characteristics and the most influential papers in the field were confirmed by developing and proposing for the first time a novel graphical tool. Instead, to address RQ2, a co-word network analysis was carried out [24] to investigate the main themes related to the analyzed topic and the driving research streams. Specifically, the co-occurrence of authors’ keywords was examined. As far as the software packages used to perform the bibliometric review, three tools were used to elaborate statistics about publications, and citations of countries/journals/authors (RQ1) and investigate the authors’ keywords (RQ2): *Microsoft Excel™, Bibliometrix* (*R*-tool), and *VOSviewer*.

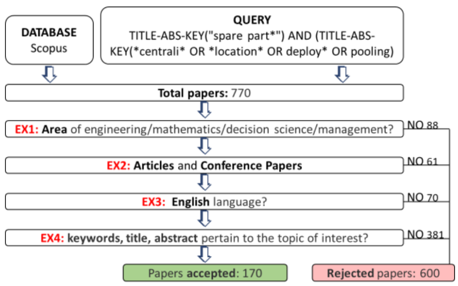

Fig. 1. SLNA performed to achieve the analyzed database

III. Results and Discussion

The database is composed of 170 documents (66% Articles and 34% Conference Papers), published by 413 authors in 109 journals in a time span of 91 years (1931-2022). The average number of citations per document is 17.8 citations/paper and the total number of citations per year is shown in Fig. 2 (orange line) together with the temporal distribution of publications (blue histograms). In Fig. 2, the first paper published is a technical document dated back to 1931 [25], where the US Military Defence mentioned for the first time the concept of centralizing spare parts inventory as an opportunity to optimize maintenance operations. However, Fig. 1 clearly shows that the effective starting date for the publication of the papers is 1960, which validates the developed search query. Indeed, 1960 is precisely the year that Das and Tyagi [17] indicated as the beginning of the research stream on the topic of stocks’ deployment and the choice between centralization and decentralization. Moreover, the evolution of publications and citations over time (Fig. 2) proves that the concept of spare parts centralization has been known to researchers for over 90 years.

However, the literature on this topic is rather lacking, especially until 2008. In fact, the average annual publication rate is relatively low (1.9 papers/year), and the percentage of documents published before 2008 is only 15.3%. However, the publication trend is strongly increasing, revealing an augmented interest of the scientific community towards this topic. Indeed, a spike in the publications curve has been recorded in the last 5 years (41.2% of papers) with a peak in 2021. Note that Fig. 2 shows only 2 articles published in 2022, but this is because the search query was conducted in February 2022. Therefore, it is reasonable to expect a significant increase of publications by the end of the year. Finally, Fig. 2 shows a remarkable peak in the citation curve during 2014, suggesting that one or more significant contributions were published on that year.

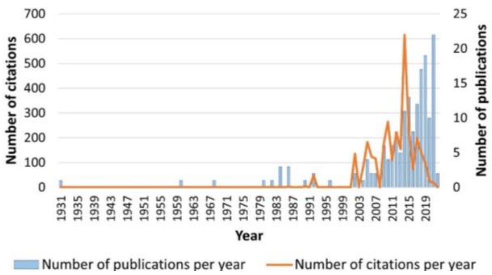

Fig. 2. Reference publication (blue) and citation (orange) year spectroscopy

A. Publication and citation analysis

To answer RQ1, first, the geographical distribution of publications and citations was studied, defining the most productive and influential countries. Fig. 3 shows the countries' productivity based on their total number of publications on the topic of spare parts deployment and inventory centralization or decentralization. Darker colors are associated to China, Germany, Netherlands, and Italy, being the most productive countries with 138, 45, 43, and 43 publications, respectively. Moreover, as a matter of fact, Fig. 3 shows that both Eastern and Western countries contribute to publishing in the analyzed field, while Africa does not concur significantly to the research development. Instead, in terms of citations, Finland, United States, and Netherlands are the most influential countries, with 779, 473, and 397 citations, respectively. Comparing the most productive and most influential countries, it emerges that the only country leader in both fields is the Netherlands. This proves that not always the countries with a high number of publications provide scientific contributions considered interesting by other researchers. Hence, it is revealed the importance of not limiting a literature analysis to the most productive countries in the field, but also extending the investigation to other less prolific countries. This consideration also applies to authors, and journals, explaining why both productivity and influence of countries/authors/journals were analyzed in this work.

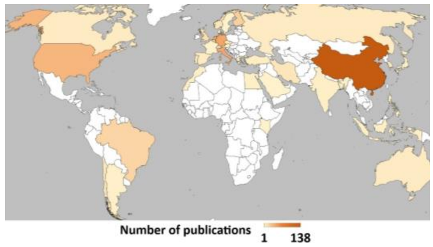

Fig. 3. Total number of publications per country

Subsequently, to identify the most productive and influential journals, three analyzes were performed. First, the journals mostly devoted to the considered topic were determined based on Bradford's Law [26]: if journals containing papers on a given topic are arranged in descending order of publications, then successive zones of journals containing the same number of papers on the topic will form the geometric series $1{:}\,n{:}\,n^2{:}\,n^3{:}\,....$ Fig. 4 shows the achieved results, indicating as the most productive journals (core sources) the ones situated in the first zone of Bradford's ranking (grey rectangle, Fig. 4): Eur. J. Oper. Res. (EJOR, 14 publications), Int. J. Prod. Econ. (IJPE, 8 publications), Comput. Ind. Eng. (CAIE, 5 publications), Int. J. Prod. Res. (IJPR, 5 publications), Proceedings of the Int. Conf. on Ind. Eng. and Oper. Manag. (Proceedings of IEOM, 5 publications), IEEE Access (4 publications), IOP Conference Series: Mater. Sci. Eng. (4 publications), IFAC-Papersonline (3 publications), IFIP Adv. Inf. Commun. Technol. (IFIP AICT, 3 publications), Int. J. Logist. Syst. Manag. (IJLSM, 3 publications), and J. Oper. Res. Soc. (JORS, 3 publications). These 11 core sources (out of 109 journals) globally contain 57 papers, covering one-third (34%) of the analyzed database.

As a second analysis, the publication trend of the top 5 core sources was defined (Fig. 5). EJOR showed a high persistence, being the only journal with regular publications over the time (especially in the last 15 years). However, CAIE, IJPR, and the Proceedings of IEOM confirmed their significance, revealing a marked interest in the topic in the last decade. Conversely, IJPE showed declining interest, producing only 2 papers in the last 11 years.

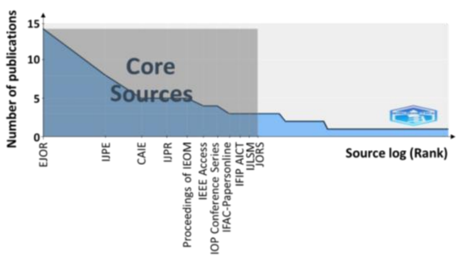

Fig. 4. Most productive journals according to Bradford's law

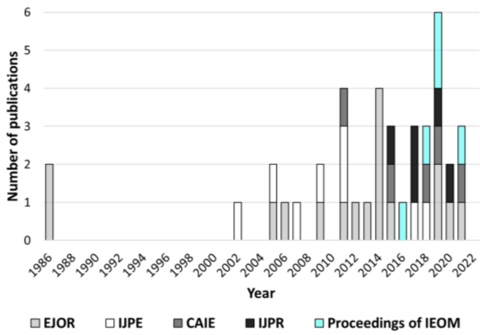

Fig. 5. Publication trend of the top 5 core sources

Since Bradford's Law highlights the most productive journals, but not the most influential ones, a third analysis was conducted, calculating the journals’ average number of Citations Per Publications (CPP, Eq. 1).

$$CPP = \frac{Total\ number\ of\ citations}{Total\ number\ of\ publications} \quad (1)$$

Hence, the most influential sources were identified as the ones with the highest CPP (Tab. 1 lists the top 5). Based on Tab. 1, it is worth noting two aspects. First, the CPP analysis allowed identifying not only the most influential journals, but also the most significant papers in the field. For instance, the contribution by Computers in Industry [27] was highlighted, receiving 400 citations in 8 years, and confirming the peak in citations noted in Fig. 2. Secondly, none of the journals in Tab. 1 appears in Fig. 4-5, pointing out that the most significant literary contributions were not published in the core sources and remarking the difference between the most productive and most influential journals.

TABLE I
TOP 5 MOST INFLUENTIAL JOURNALS BASED ON CPP

Source (with references)	Number of publications	Number of citations	CPP
Comput. Ind. [27]	1	400	400
J. Manuf. Technol. Manag. [28][29]	2	276	138
Rel. Eng. Syst. Saf. [30]	1	86	86
Prod. Plan. Contr. [31][32][33]	3	255	85
IIE Transactions[34]	1	81	81

Finally, the most productive and influential authors were identified considering their publications and CPPs, and proposing a novel graphical descriptive tool (called *Qualitative Authors' Relevance Assessment - QARA*), which summarizes the main information on authors’ productivity and influence. The QARA is shown considering the top 15 authors in terms of CPP (Fig. 6). However, it could be extended to all authors. In the QARA, a dot is used to describe the annual publications provided by each author. Specifically, the dots’ size can be small, medium or large according to the number of annual documents published by each author (1, 2, or 3, respectively). The dots’ color follows a chromatic scale based on the total number of annual citations received by each author (dark blue corresponds to 1 citation, while dark red corresponds to 10). Finally, the authors’ names are ranked on the y-axis in descending order of CPP.

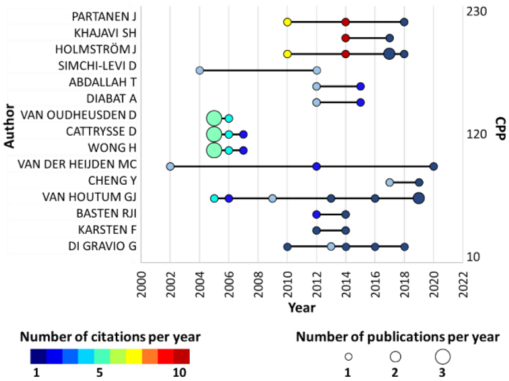

Fig. 6. Qualitative Authors’ Relevance Assessment

From the QARA (Fig. 6), four considerations emerge that are useful for answering RQ1. First, the most productive authors in the field appear based on the total number of publications (number and size of dots). In particular, the most productive author is Van Houtum, with a total of 7 publications. Secondly, the most influential authors are identified based on the highest CPPs, recognizing Partanen, Khajavi, and Holmström as the top 3 authors in the y-axis (with CPP equal to 224.3, 201.5, and 135.6, respectively). This result shows the difference between most productive and influential authors. Thirdly, looking at the dots’ distribution and size, it is possible to check the temporal publication trend of each author, also observing the publication cadence and the date of the first publication. Finally, it is possible to identify the most influential papers in the existing literature on the analyzed topic. As instance, in the upper part of Fig. 6, the papers characterized by the highest CPP are shown. Moreover, three red dots and two yellow dots both of small size (1 publication associated with each dot) are clearly visible, corresponding to the contributions with the highest number of citations [27], [28]. It is worth noting that these two most influential publications deal with the same topic, thus suggesting an emerging research stream in the analyzed field. Such emerging stream is to investigate the impacts of Additive Manufacturing (AM) on the SC configuration process, also considering the possibility of removing spare parts inventories by setting decentralized SCs, where each DC owns its 3D-printer for producing items on-demand.

B. Co-word network analysis

To answer RQ2, first, the main themes related to the topic of inventory centralization/decentralization and the deployment of spare parts in DCs were examined by studying the co-occurrence of authors' keywords in *VOSviewer*. Results are shown in Fig. 7, where keywords with a minimum number of co-occurrences of 2 are mapped together with their reciprocal links. Based on the colors and keywords of Fig. 7, 5 main research themes were identified related to the analyzed topic, which were confirmed by consulting the abstract of the database papers: (pink) the optimal deployment of spare parts in SCs with single or multi-location DCs and two or multiple echelons; (red) AM as an opportunity to switch from centralized to decentralized SCs, changing the spare parts deployment in SCs; (yellow) the optimization of spare parts deployment to improve maintenance activities in the sectors of aeronautics and military industry; (brown) the design of spare parts deployment in SCs where emergency and lateral shipments are allowed; (green) sustainability and reverse logistics with a focus on spare parts deployment in SCs.

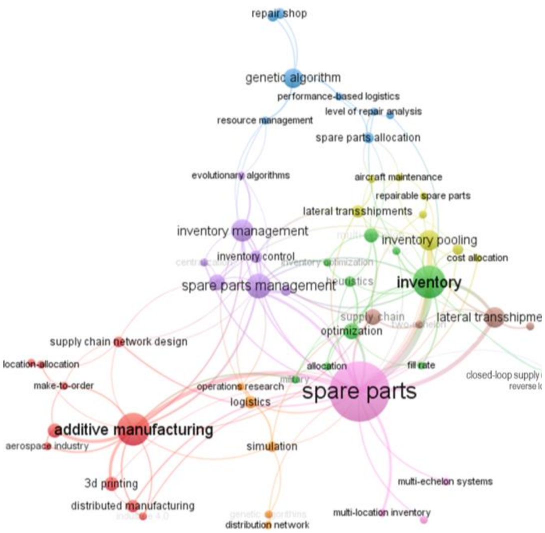

Fig. 7. Co-occurrence of authors' keywords

Finally, the answer to RQ2 was completed by building a Thematic Map of authors' keywords following Cobo et al. [35] and using *Bibliometrix* (Fig. 8). Besides confirming the results of Fig. 7, Fig. 8 emphasized two driving (motor) themes that mainly concur in developing the research on the analyzed topic: the design of spare parts deployment in closed-loop SCs and the design of spare parts deployment with AM spare parts. In addition to this, Fig. 8 can also be used to define well-established (basic) themes on the analyzed topic, as well as some niche themes and emerging or declining research streams. Based on this, another consideration appears regarding the methods used by researchers to plan the spare parts deployment: while exact optimization models are widely used in the literature, simulation models seem to be scarcely proposed (emerging or declining themes), and heuristic optimization models are still partially considered a driving theme for research development. Concerning heuristic models, Fig. 8 underlines the authors' interest in using genetic algorithms to optimize the spare parts deployment and the SC configuration.

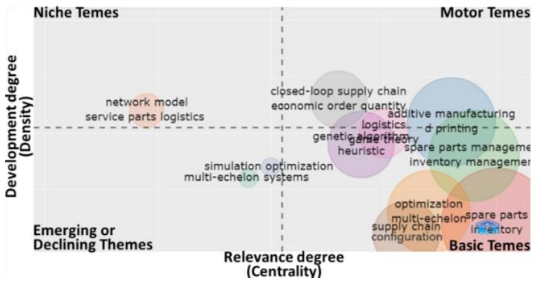

Fig. 8. Thematic Map of authors' keywords

IV. Conclusions

This paper explores the extant literature on the topic of inventory centralization or decentralization and the deployment of spare parts in DCs (step 1 of SC configuration). Based on the numbers of publications and citations and developing a novel graphical tool (here called QARA), the most productive and influential countries, journals, and authors, as well as the 2 most influential contributions in the field were identified. Subsequently, the main themes related to the analyzed domain were investigated based on the co-occurrence of authors' keywords, also determining what are the driving research streams that mainly contribute to developing the literature in the considered field. Results prove that, despite it has been almost 100 years since the considered topic was first mentioned, the literature in this field is rather lacking (especially until 2008). However, such a topic is attracting the attention of researchers in the last 10 years. Specifically, researchers are mainly interested in 2 driving research streams: (i) planning the deployment of spare parts by considering sustainability issues and on closed-loop SCs; (ii) evaluating the impact of AM in SCs, exploiting its advantages to optimize the spare parts deployment. Besides, concerning the methods used to define the spare parts' deployment, results show that exact optimization models are widespread among the documents in the analyzed domain. Conversely, simulation models are rarely used, while heuristic optimization models seem driving elements, which favor the development of research in the considered field. Finally, results underline the difference between the most productive and most influential countries, journals, and authors, underlining the importance of studying both.

Limitations of this research are related to having manually screened the sources of the dataset used for developing the bibliometric review. This was necessary since different semantic meanings were associated with the term "location" and its synonyms, leading to articles not relevant to the analyzed topic. Instead, the contribution of this work is to outline the characteristics of the current body of knowledge on the considered topic, enabling researchers to identify gaps in the literature, thus discovering future research opportunities. Future developments of this work could be two. First, to consult other databases in addition to Scopus to validate or deepen the bibliometric review. Secondly, to expand the systematic literature analysis by consulting in detail all the dataset papers, defining appropriate clusterization criteria to analyze them based on different perspectives.

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A data-driven methodology for the dynamic review of spare parts supply chain configuration

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Abstract

An efficient supply chain (SC) configuration allows the success of spare parts retailers. Configuring spare parts SCs involves defining two aspects: the stock deployment into distribution centres (DCs) (i.e., inventory centralisation or decentralisation) and the stock supply in each DC (how many spare parts to supply and how often). Given the unpredictability of spare parts demand, stock deployment and supply policies should be regularly reviewed, adapting to fluctuations in customer needs. A viable way to do so is to adopt a multi-criteria ABC criticality classification. However, the multi-criteria ABC criticality classification has often been used to plan stock supply policies in a single DC, but only once to plan spare parts deployment. Nevertheless, the available literature methodology presents major limitations, being not applicable in real companies. Therefore, this paper provides a novel methodology, called SP-LACE, which, first, reviews the configuration of spare parts SCs based on a multi-criteria criticality classification. Then, allows, for the first time, evaluating the economic benefits of the reviewed SC configuration. SP-LACE was tested on two case studies and compared to the literature methodology. The results show that it provides economic benefits in terms of SC total costs, also overcoming the limitations of the literature methodology.

Keywords

Supply chain configuration review; Spare parts logistics; Multi-criteria inventory classification; Inventory management; Inventory allocation.

Declaration of interest

None

1. Introduction

Spare parts retailers have identified as ever-growing crucial aspects for their success the adoption of a customer-centric perspective and the proper management of customer needs in supply chains (SCs) (Esmaeili et al., 2021; Giannikas et al., 2019). As stated by Stoll et al. (2015), a good way to increase the serviceability of spare parts retailers is to optimally configure SCs, ensuring the alignment between stocks in distribution centres (DCs) and spare parts demand. However, configuring spare parts SCs is not an easy task since a typical challenge is to minimise inventory costs while facing demand volatility and guaranteeing high service levels (Jiang et al., 2019). Given this challenging context, spare parts retailers should embrace structured methodologies for configuring SCs (Cantini et al., 2022; Ahmed et al. 2022).

According to Manikas et al. (2019) and Gregersen and Hansen (2018), a sound SC configuration methodology should focus on defining two aspects of primary importance: the optimal stock deployment and the optimal stock supply policy to be adopted for each individual Stock Keeping Unit (SKU). Concerning the optimal stock deployment (first decision of SC configuration), two antithetical strategies can be distinguished, namely centralisation and decentralisation. A decentralised stock deployment implies storing the SKUs into multiple independent DCs, each meeting the demand of local customers. As a result, SC flexibility, SC responsiveness, and low outbound transportation costs are ensured (Milewski, 2020), but leading to high holding costs since many DCs are managed, each needing to guarantee high service levels. Conversely, a centralised stock deployment involves storing all SKUs into a single DC which serves all the customers, determining reduced holding and ordering costs (due to the "risk-pooling" effect), but to the detriment of SC flexibility, SC responsiveness, and transportation costs (Schmitt et al., 2015; Li et al., 2019). Instead, concerning the stock supply policies (second decision of SC configuration), in each DC, it is established which SKU to keep in stock and which to order on-demand, as well as how many stocks to supply and how often (Yazdekhasti et al., 2022).

Due to the volatility of spare parts demand, Del Prete and Primo (2021) and Van der Auweraer and Boute (2019) suggested that spare parts SCs should not be configured only once (when the business is born), but periodically. Indeed, regularly reviewing the SC configuration over time allows adapting the stock deployment and supply policies to changes in spare parts demand. As a result, the inventory levels in DCs are optimised by minimising holding and ordering costs, while ensuring high service levels, which reduce stock-outs and backorder costs (Eldem et al., 2022; Alfieri et al., 2017). For this reason, Cantini et al. (2021) recommended spare parts retailers to reject static SCs configuration methodologies, while preferring the dynamic ones (also called Dynamic Asset Deployment methodologies (Cohen et al., 2006)), which allow the SC configuration to be regularly reviewed based on spare parts demand fluctuations. Nevertheless, as reported by Hu et al. (2018), many spare parts retailers are far from implementing methodologies to review their starting SC configuration and quite often, instead, the SC configuration is chosen only one time and never questioned. Therefore, the stock deployment and supply policies continue to be static, arbitrary, and based on experience, and a quick and easy-to-use methodology for reviewing the SC configuration in spare parts retail companies is greatly needed (Basto et al., 2019).

According to several authors (Sheikhar and Matai, 2022; Teunter et al., 2010), a valuable way to address this gap is to define heuristic methodologies for reviewing the SC configuration based on spare parts criticality classification techniques. Indeed, two main reasons make the spare parts criticality classification techniques particularly suitable for this purpose. First, Basto et al. (2019) and Zhang et al. (2001) reported that the criticality classification techniques require few investments in computational resources and advanced technologies, which are still lacking in many enterprises. Secondly, Manikas et al. (2019) and Amirkolaii et al. (2017) stated that spare parts SCs are typically characterised by a high variety of SKUs, but the computational cost and complexity associated with optimising the SC configuration for each individual SKU through exact optimisation techniques is practically not feasible. Hence, spare parts criticality classification techniques are preferable since they suggest similar stock deployment and supply policies for all SKUs belonging to the same criticality class, without performing individual SKUs analyses (Braglia et al., 2004). In this context, due its simplicity and popularity, Amirkolaii et al. (2017) and Persson and Saccani (2007) suggested the multi-criteria ABC criticality classification as a successful solution for reviewing the spare parts SC configuration. However, Mehdizadeh (2020) and Roda et al. (2014) showed that the multi-criteria ABC criticality classification has been widely used by spare parts retailers mainly to plan the optimal stock supply policies in a single DC. Contrarily, it has been barely used to plan stock deployment policies in multiple DCs.

To the best of the authors' knowledge, Stoll et al. (2015) were the only ones to propose a methodology based on a multi-criteria ABC criticality classification for planning both stock deployment and supply policies in the DCs of a spare parts retail company. However, as stated by Stoll et al. (2015), their methodology is characterised by some limitations that hinder not only its applicability in real cases, but also its suitability for regularly reviewing the SC configuration (which is necessary in spare parts SCs). Therefore, a quick and easy-to-use methodology to review both the stock deployment and supply policies (i.e., SC configuration) in DCs based on a multi-criteria ABC criticality classification is currently missing. Moreover, Stoll et al. (2015) lack an economic analysis of the benefits achievable (in terms of holding, ordering, and backorder costs) by reviewing the spare parts SC configuration. Consequently, the effectiveness of this methodology is not demonstrated, as well as the importance of reviewing the spare parts SC configuration.

To fill these gaps, this paper proposes a novel methodology, which from now on will be referred to as "SP-LACE – Spare Parts suppLy chAin Configuration rEview". SP-LACE represents the first methodology based on a multi-criteria ABC criticality classification of spare parts, which is suitable for regularly reviewing the configuration of spare parts SCs in a quick and easy-to-use way. SP-LACE is composed of two stages. In stage 1, the optimal stock deployment and supply policies are suggested for each SKU, searching (through a data-driven analysis) for a trade-off between holding, ordering, and backorder costs in DCs. Then, in stage 2, for the first time in the literature, the economic benefits of the reviewed spare parts SC configuration are evaluated, comparing the achieved SC total cost (which includes holding, ordering, backorder costs, as well as the costs incurred to perform the review process) with the same cost in the starting SC configuration (before the review process).

The remainder of the present paper is as follows. Section 2 provides a literature review regarding the use of multi-criteria ABC criticality classifications to review the configuration of spare parts SCs. In Section 3, SP-LACE is presented. In Section 4, SP-LACE is tested on two case studies, showing how the reviewed SC configuration improves the economic performance of DCs compared to the starting (historical) SC configuration. Besides, SP-LACE is also compared to the existing literature methodology by Stoll et al. (2015) to show how it overcomes the latter's limitations. Finally, in Section 5, some conclusions are offered.

2. Literature review

According to Ding and Kaminsky (2020) and Mangiaracina et al. (2015), the methodologies for reviewing the configuration of spare parts SCs fall under three categories: exact optimisation, heuristic optimisation, and simulation methodologies. As discussed before, when looking for a quick and easy-to-use methodology for reviewing the spare parts SC configuration, the literature suggests adopting heuristic methodologies, especially those based on spare parts criticality classification techniques (Gregersen and Hansen, 2018; Cohen et al., 1990). More in detail, among the existing spare parts criticality classification techniques, Amirkolaii et al. (2017), and Persson and Saccani (2007) suggested to adopt a multi-criteria ABC criticality classification, which, due to its user-friendlyiness, it is still the most commonly employed technique in real companies (Gong et al., 2022; Xu and Xu, 2021). According to Van Wingerden et al. (2016) and Persson and Saccani (2007), a methodology to review the configuration of spare parts SCs should consist of two steps. First, to create spare parts classification classes (A – critical SKUs, B – moderately criticals, and C – non criticals) by differentiating the SKUs' criticality based on predefined criticality criteria and relying on Pareto's principle. Concerning this, Xu and Xu (2021) and Kauremaa and Holmström (2017) reported that, due to the heterogeneous nature of spare parts, a multi-criteria ABC criticality classification should be preferred to a mono-criterion one, and the spare parts demand should be included among the considered criticality criteria (correlating it to the importance of stocking specific SKUs in DCs). Subsequently, to use the class membership for guiding rule-based SC configuration decisions, thus defining appropriate stock deployment and supply policies for each class, such as complex control methods for the most critical SKUs and simpler procedures for the remaining ones (Chen, 2011; Chen et al., 2008). By repeating this procedure during the business lifetime, the SC configuration can be reviewed, aligning it with customer needs, rationalising the use of economic resources, and avoiding investments in non-critical spare parts (Cohen et al., 1999).

However, despite the potential effectiveness of a quick and easy-to-use methodology for reviewing the spare parts SC configuration based on a multi-criteria ABC criticality classification, Mehdizadeh (2020) and Roda et al. (2014) showed that the multi-criteria ABC criticality classification has been used mainly for planning the stock supply policies in a single DC (first decision of SC configuration), without suggesting any stock deployment policy (second decision of SC configuration). Indeed, concerning the stock supply policies in a single DC, Flores and Whybark (1986) introduced the first multi-criteria ABC criticality classification, which implies performing three steps. First, developing two mono-criterion ABC criticality classifications (using as criticality criteria the SKUs' unitary cost and procurement lead time). Secondly, combining the results of the two classifications to generate a "joint-criteria matrix", classifying SKUs into nine criticality classes. Finally, associating optimal stock supply policies with the SKUs belonging to each class, where non-critical SKUs are ordered on-demand, while critical and moderately critical SKUs are kept in stock. After Flores and Whybark, many other authors proposed approaches to plan the stock supply policies in a single DC based on a multi-criteria ABC criticality classification, such as Petrović and Petrović (1992), Celebi et al. (2008), Lukinskiy et al. (2020), and Sheikhar and Matai (2022). In this context, not only approaches to plan the stock supply policies based on the sole use of ABC analyses were suggested, but also approaches based on the combined use of multi-criteria ABC criticality classifications with other criticality classification techniques, such as the Analytic Hierarchy Process (AHP) (Stoll et al., 2015), Artificial Neural Networks (ANN) (Partovi and Anandarajan, 2002), genetic algorithms (Durán et al., 2019; Yu, 2011), failure mode effect and criticality analysis (FMECA) (Gong et al., 2022), fuzzy classifications (Luluah et al., 2020; Chu et al., 2008), and Data Envelopment Analysis (DEA) (Ramanathan, 2006).

On the contrary, concerning the stock deployment policy, the multi-criteria ABC criticality classification has rarely been used. Indeed, Cantini et al. (2021) and Huiskonen (2001) confirmed that the existing methodologies based on multi-criteria ABC criticality classifications focus on optimising the stock supply policies in a single DC, while overlooking the stock deployment policies. Manikas et al. (2019) and Mangiaracina et al. (2015) confirmed this by stating that, although spare parts deployment policies are key-drivers of the overall profitability of a company, the problem of choosing between centralisation and decentralisation of SKUs in multiple DCs is not yet sufficiently explored and there is a lack of practical solutions to address it. To the best of the authors' knowledge, only one heuristic methodology based on a multi-criteria ABC criticality classification has been proposed for planning both the stock deployment and supply policies in multiple DCs (Stoll et al., 2015). Such a methodology relies on developing a three-criteria criticality classification of spare parts. Specifically, two criticality criteria (unitary cost and coefficient of variation of demand) are used to estimate the SKUs' value and the demand predictability (performing an HML and an XYZ analysis, respectively). Then, the third criticality criterion is used to classify SKUs based on the impact of spare parts unavailability on the maintenance and production performance of the system (using a VED analysis, a decision tree, and an AHP). However, Stoll et al. (2015) pointed out that their methodology is characterised by two major limitations, which hamper its applicability in real companies and its suitability for regularly reviewing the spare parts SC configuration. First, a large amount of data have to be collected, which are hardly available in company databases. Secondly, maintenance experts have to be consulted, making the methodology application time-consuming, and its SC configuration results not entirely data-driven but rather affected by subjectivity. In addition, Stoll et al. (2015) lack an economic analysis to evaluate the benefits achievable by reviewing the configuration of spare parts SCs. In fact, no comparison is provided between the holding, ordering, and backorder costs in the reviewed SC configuration and the same costs in the starting SC configuration (before the review process). Besides, the costs incurred to review the SC configuration are completely neglected. As a result, the effectiveness of the methodology by Stoll et al. (2015) is not demonstrated, as well as the importance of reviewing the spare parts SC configuration.

Aiming to fill the identified gaps, the SP-LACE methodology was developed, which will be described in the next Section. SP-LACE represents the first quick and easy-to-use methodology based on a multi-criteria ABC criticality classification of spare parts, which is suitable for reviewing the configuration of spare parts SCs. For each individual SKU, SP-LACE allows planning both the optimal stock deployment policies and supply policies. Moreover, SP-LACE is a data-driven methodology, which relies on the analysis of data usually available in companies. Therefore, SP-LACE provides results not affected by subjectivity and it is applicable in real companies. Finally, SP-LACE allows performing an economic evaluation of the reviewed SC configuration. Hence, it allows demonstrating the importance of regularly reviewing the spare parts SC configuration and the cost benefits achievable in the reviewed SC configuration over the starting SC one (in terms of SC total cost, which is take as the sum of holding, ordering, backorder, and review costs).

3. SP-LACE methodology

The SP-LACE methodology was developed to optimise stock deployment and supply policies within existing two-echelon SCs, where spare parts retailers already own DCs and are willing to review the starting SC configuration (Cantini et al. 2022). Two-echelon SCs are considered since the multi-echelon ones have been reported to be uncommon in the field of spare parts retail (Cantini et al., 2021; Botter and Fortuin, 2000). However, SP-LACE can also be applied in multi-echelon SCs by splitting them into a series of two-echelon SCs. SP-LACE is composed of two stages. In stage 1, the SKUs' criticality classification is performed according to two criticality criteria: the SKUs' value and the predictability of their demand, which are assessed through an HML and an XYZ analysis, respectively. Based on the achieved classification, each criticality class is associated with optimal stock deployment and supply policies. In this way, the management of multiple SKUs in multiple DCs is aligned with the spare parts demand, and an optimal SC configuration is found, which determines a trade-off between holding, ordering, and backorder costs. SP-LACE is a data-driven methodology, which relies entirely on the analysis of objective data usually available in companies, without needing to consult maintenance experts or perform qualitative analyses (e.g., VED analysis or AHP). Consequently, SP-LACE overcomes the limitations of the literature methodology by Stoll et al. (2015) since two beneficial side effects are obtained. First, SP-LACE provides results not affected by subjectivity. Secondly, the application of SP-LACE is not time-consuming, allowing the management of thousands of SKUs and enabling regular reviews of the SC configuration. In addition, SP-LACE, unlike the methodology by Stoll et al. (2015), includes an economic evaluation of the performance of the reviewed SC configuration. Indeed, in stage 2 of SP-LACE, the total cost of the reviewed SC (including holding, ordering, and backorder costs, as well as the cost incurred to carry out the review process) is compared with the one of the starting SC (before the review process), seeking to show the achieved benefits and the importance of reviewing the SC configuration.

Before describing SP-LACE, the assumptions on which it relies are listed, reporting the scientific contributions on which they are based:

- DCs are assumed to have an unlimited capacity (Tapia-Ubeda et al., 2020);
- No costs related to the purchase or rental of DCs are considered, since spare parts retailer already own DCs (Cantini et al. 2022);
- No inbound and outbound transportation costs are considered, being negligible compared with other SC costs (Cohen et al., 1988);
- No issues related to spare parts sustainability and closed-loop SCs are considered (Zijm et al., 2019);
- Lateral transshipments are treated as described in Appendix A;
- Spare parts procurement lead times are assumed deterministic (Lolli et al., 2022), while spare parts demand is assumed stochastic (Liu et al., 2014). Specifically, based on Syntetos and Boylan (2006), and the Italian National Standard (Italian Technical Commission for Maintenance, 2017), SP-LACE considers a normal distribution for SKUs with an average demand during the procurement lead time greater than 15 units, while considering a Poisson distribution for the other SKUs. In this sense, SP-LACE improves the methodology by Stoll et al. (2015), which imposes a normally distributed demand for all SKUs;

In the following, SP-LACE is presented, showing, in Section 3.1, how to apply the methodology for reviewing the spare parts SC configuration (stage 1), then, in Section 3.2, how to evaluate the economic benefits of the reviewed SC configuration (stage 2). The relevant parameters on which SP-LACE relies are summarised in Table 1. Moreover, Table 2 lists the cost items considered to evaluate the economic benefits of the reviewed SC and assess the performance of SP-LACE.

Table 1. Summary of SP-LACE parameters.

Parameter	Description	Unit measure
r	Considered SC configuration. r is 0 in the starting SC configuration, while being 1 in the reviewed SC configuration	[-]
i	Considered DC. i assumes integer values between 1 and the total number of DCs ($\#DCs$)	[-]
k	Considered SKU. k assumes integer values between 1 and the total number of SKUs ($\#SKUs$)	[-]

$Period\ of\ analysis$	Time interval considered to evaluate the cost performance of the SC	[time]
uc_k	Unitary cost of purchasing each SKU from the supplier	[€/unit]
$h_{\%}$	Holding cost rate for keeping inventory of SKUs in the period of analysis. According to Khajavi et al. (2014), it includes the obsolescence rate of SKUs	[time^{-1}]
$X_{i,k,r}$	Total demand received for each SKU in each DC in the period of analysis. It depends on the demand distribution $x_{i,k,r}$, which can be a normal or a Poisson one, as already explained	[units/time]
$\overline{x_{i,k,r}} * LT_{i,k}$	Average demand received for each SKU in each DC during the procurement lead time	[units]
$\sigma(x_{i,k,r})$	Standard deviation of the demand for each SKU in each DC during the period of analysis. It is considered when the demand distribution ($x_{i,k,r}$) is a normal one	[units/time]
$LT_{i,k}$	Procurement lead time of each SKU in each DC	[time]
$\#Ord_{i,k,r}$	Number of supply orders issued by the analysied company in the period of analysis to replenish each SKU in each DC	[supply orders/time]
$QOrd_{i,k,r}$	Total quantity of each SKU ordered by the analysed company to replenish each DC in the period of analysis	[units/time]
oc_k	Cost of issuing one supply order for a SKU	[€/supply order]
$uback_k$	Unitary backorder cost of each SKU	[€/backorder]
$SL_{i,k,r}$	Desired service level for each SKU in each DC	[-]
$Q'_{i,k,r}$	Optimal order quantity of each SKU in each DC	[units]
$ROP'_{i,k,r}$	Reorder level associated with each SKU in each DC	[units]
$SS_{i,k,r}$	Safety stocks of each SKU in each DC	[units]
$Z_{i,k,r}$	Service factor associated with the desired service level ($SL_{i,k,r}$) in a standardised normal distribution	[-]
$cost\_limit_k$	Threshold value established based on the type of spare parts retailed by the analysed company	[€]
tc	Average time required to run the stage 1 of SP-LACE and update its mathematical calculations	[time]
$\#\gamma\ SKU_{depl_{i,r}}$	Number of γ SKUs in each DC, whose deployment policy changes when moving from the starting SC configuration to the reviewed one	[-]
$\#trips_r$	Number of displacements to be performed in the reviewed SC configuration to move stocks from decentralised DCs to the central one	[-]
$\#SKU_{supply_{i,r}}$	Number of SKUs in each DC, whose supply policy changes when moving from the starting SC configuration to the reviewed one	[-]
mh	Cost of manpower who applies SP-LACE, updating its mathematical calculations and the consequent stock deployment and supply policies associated with SKUs	[€/time]
$dist$	Average distance between the central DC and the decentralised ones in the analysed company	[km]
Cap	Capacity of the vehicle used by the analysed company to displace SKUs between DCs and deliver them to customers	[m^3]
vol_k	Volume of each SKU	[m^3]
$utrip$	Cost per kilometer of the vehicle used to displace SKUs	[€/km]
tm	Average time required to update the supply policy of one SKU in the company Information Technology (IT) system	[time]

Table 2. Cost items considered in SP-LACE.

Costs	Description	Unit measure
C_{tot_r}	Total cost of the SC	[€/time]
C_{H_r}	Holding cost	[€/time]
C_{O_r}	Ordering cost	[€/time]
C_{B_r}	Backorder cost	[€/time]
C_{rev_r}	Cost incurred to review the SC configuration	[€/time]
C_{Sof}	Software cost incurred, each time the SC configuration is reviewed, to run the mathematical calculations and apply the stage 1 of SP-LACE	[€/time]
C_{Disp_r}	Displacement cost to move, in the central DC, the γ SKUs that in the starting SC configuration were decentralised and, after the SC configuration review, have to be centralised (changing their deployment policy)	[€/time]
C_{Adm_r}	Administrative cost to update, in the IT system, the $ROP_{i,k,r}$ and $EOQ_{i,k,r}$ values of the SKUs whose supply policy has changed when moving from the starting SC configuration to the reviewed one	[€/time]

3.1. Stage 1: reviewing the spare parts SC configuration

To review the spare parts SC configuration, SP-LACE implies performing in each company DC a two-criteria criticality classification of SKUs, which is achieved through an HML and an XYZ analysis, as follows.

The HML analysis is carried out to assess the SKUs' value by ranking them according to their unitary cost ($uc_{i,k,r}$, which, in spare parts retail companies, is the cost of purchasing spare parts from suppliers). To this end, the cost of each SKU is normalised with respect to the total cost of the SKUs' spectrum, and the cumulative frequency curve is developed. Then, according to the tangent method (Ultsch and Lötsch, 2015; Van Wingerden et al., 2016), the cumulative frequency curve is divided into three criticality classes (H, M, and L), thus associating each SKU with a specific class.

The XYZ analysis is performed to evaluate the predictability of spare parts demand by ranking SKUs according to their historical number of supply orders ($\#Ord_{i,k,r}$) issued in the period of analysis to replenish each DC. Specifically, the predictability is not evaluated by considering the coefficient of variation of spare parts demand (as in the methodology by Stoll et al., (2015)), but rather by ranking SKUs based on $\#Ord_{i,k,r}$ for two reasons. First, the deviation and expected value of spare parts demand are already taken into account when defining the supply policy in DCs (e.g., when calculating the reorder points of SKUs). Therefore, it is not necessary to consider them twice. Moreover, the standard deviation and expected value are parameters which typically describe a normal distribution, but the demand for many SKUs follows a Poisson distribution. As in the HML analysis, the X, Y, and Z classes are identified based on the tangent method and the cumulative frequency curve.

Combining the results of the HML and XYZ analysis, a 3x3 matrix is obtained, whose quadrants can be reclassified into three main criticality classes (α – critical, β – moderately critical, and γ – non critical), achieving the mono-criterion matrix of Figure 1 (Flores and Whybark, 1987; Frandsen et al. 2020). Specifically, SKUs belonging to HX, HY, and MX quadrants are moved into class α. Indeed, a SKU that is critical in at least one of the two classifications (HML and XYZ analyses) should be critical also in the final mono-criterion classification. For similar reasons, SKUs belonging to LY, MZ, and LZ quadrants are placed into class γ. Finally, the remaining SKUs are grouped into class β.

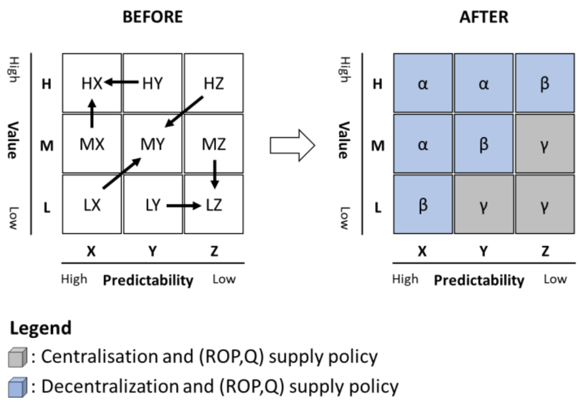

Figure 1. Transformation of the multi-criteria classification matrix (before) into a mono-criterion one (after).

At this point, the positioning of SKUs into criticality classes (α, β, and γ) is used to plan the SC configuration of each SKU in each DC, defining both optimal stock deployment and supply policies. Specifically, the SC configuration of each SKU is selected searching for a trade-off between holding, ordering, and backorder costs, as follows. A decentralised stock deployment is suggested for SKUs in α and β classes. Indeed, the storage close to peripheral customers is suggested for critical and moderately critical SKUs to reduce delivery times and backorder costs, ensuring SC flexibility and SC responsiveness (Van Wingerden et al. 2016). Besides, according to Ivanov (2021) and Emar et al. (2021), in each DC, a continuous (ROP, Q) supply policy is indicated for SKUs in α and β classes, where, ROP is the reorder level calculated to prevent stock-outs of critical and moderately critical SKUs (reducing backorder costs), while Q is the optimal order quantity which allows keeping optimal inventory levels and finding a trade-off between holding and ordering costs.

Conversely, centralisation in a single DC[1] is indicated for SKUs in γ class since they are non-critical and rarely required. Hence, their stock deployment and supply efforts should be simplified as much as possible, while benefiting from the risk-pooling effect (Mohammaditabar et al. 2012). For γ SKUs, no stock is kept in

[1] Among the DCs owned by the company, there are many ways to select the most suitable one for centralisation purposes (central DC). However, the investigation of these methods is beyond the scope of this study. Hence, we only mention that the central DC can be selected by applying techniques such as those by Farahani et al. (2015) and Fathi et al. (2021), or simply by identifying the facility with the largest size and centrality to customers.

decentralised DCs, while the central DC should keep stocks based on an (ROP, Q) policy, facing the demand of all customers (i.e., cumulated local and peripheral requests).

The application of the stage 1 composing SP-LACE is schematically summarised in Figure 2, which refers, as an example, to a company with 3 DCs (DC_1, DC_2, and DC_3, see Step 0, Figure 2), where DC_2 is assumed as central DC. As depicted in Figure 2, to review the SC configuration, the following steps are performed:

- In Step 1, the multi-criteria criticality classification of spare parts (HML and XYZ analyses) is accomplished in peripheral DCs (DC_1 and DC_3), associating SKUs with α, β, or γ criticality classes;
- In Step 2, the stock deployment policies are defined, indicating to centralise non-critical γ SKUs, while keeping decentralised the α and β ones;
- In Step 3, the demand for γ SKUs is cumulated with the demand already faced by the central DC, the multi-criteria criticality classification of spare parts is carried out in DC_2, and SKUs in DC_2 are associated with α, β, or γ criticality classes;
- Finally, in Step 4, the stock supply policies are defined in each DC. No stock is kept for γ SKUs in DC_2 (since they are non-critical both in the peripherals and central DC). Instead, optimal quantities are kept in stock for the remaining α and β SKUs based on the (ROP, Q) supply policy, which is defined as reported below.

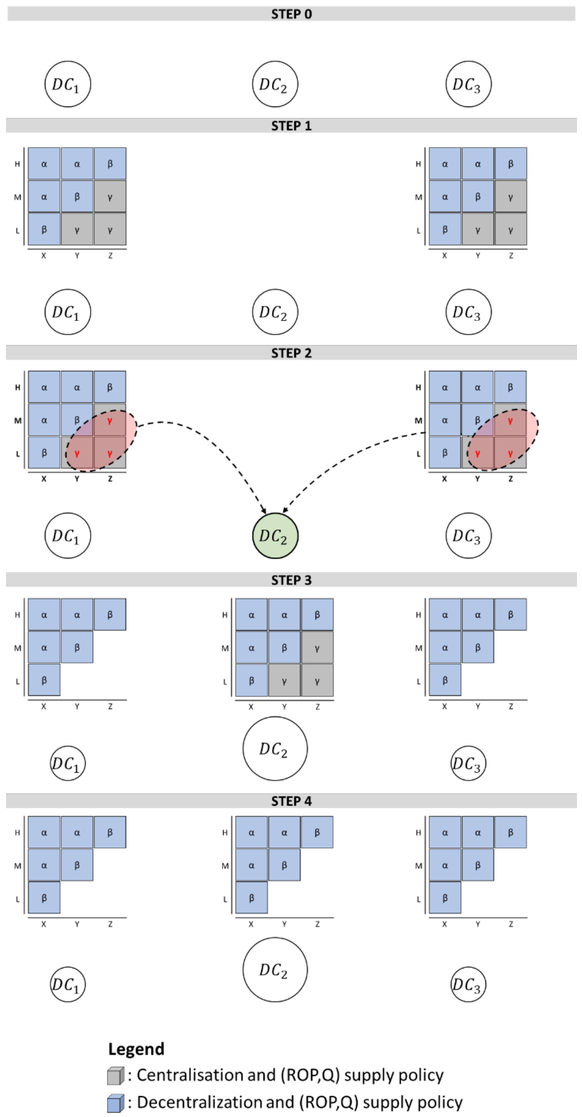

Figure 2. Example application of stage 1 of *SP-LACE*. A detailed description of the Steps composing this figure is provided in the text.

To calculate the optimal (ROP, Q) supply policy associated with each SKU (k) in each DC (i) in the considered SC configuration (r), first, the values of reorder level $(ROP_{i,k,r})$ and optimal order quantity $(Q_{i,k,r})$ are initialised using Equations 1 and 2, respectively.

$$ROP_{i,k,r} = \left(\overline{x_{i,k,r}} * LT_{i,k}\right) + SS_{i,k,r} \tag{1}$$

$$Q_{i,k,r} = \sqrt{\frac{2 \cdot X_{i,k,r} \cdot oc_k}{h_{\%} \cdot uc_k}} \tag{2}$$

Where $SS_{i,k,r}$ are the safety stocks (Equation 3) calculated to compensate demand fluctuations of each SKU (k) in each DC (i) with the desired service level.

$$\begin{cases} SS_{i,k,r} = Z_{i,k,r} * \sqrt{LT_{i,k}} * \sigma(x_{i,k,r})\ if\ k\ has\ a\ normal\ demand \\ 1 - \sum_{n=0}^{SS_{i,k,r}-1} \left[\frac{(\overline{x_{i,k,r}} * LT_{i,k})^n}{n!} * e^{-(\overline{x_{i,k,r}} * LT_{i,k})} \right] \geq (1 - SL_{i,k,r})\ if\ k\ has\ a\ Poisson\ demand \end{cases} \tag{3}$$

Next, the $ROP_{i,k,r}$ and $Q_{i,k,r}$ values are transformed into $ROP'_{i,k,r}$ and $Q'_{i,k,r}$ to control the stocks in each DC and avoid excessive inventory levels or unnecessary supply orders being issued for expensive and slow-moving SKUs. Specifically, two constraints are introduced based on Alvarez and van der Heijden (2014) and Cantini et al. (2021) to achieve the final (ROP', Q') supply policy. The first constraint (Equation 4) updates the optimal order quantity ($Q_{i,k,r}$') of SKUs by imposing not to reorder more than twice the units required in the period of analysis ($X_{i,k,r}$). The second constraint (Equation 5) updates the reorder level ($ROP_{i,k,r}$') so that no stock is held for low-turnover, high-cost SKUs.

$$Q'_{i,k,r} = \begin{cases} X_{i,k,r}, if\ Q_{i,k,r} > (2 * X_{i,k,r}) \\ Q_{i,k,r},\ else \end{cases} \tag{4}$$

$$ROP'_{i,k,r} = \begin{cases} on-demand\ supply\ of\ k\ in\ i,\ if\ \#Ord_{i,k,r} \leq 1\ and\ QOrd_{i,k,r} \leq 1 \\ on-demand\ supply\ of\ k\ in\ i,\ if\ \#Ord_{i,k,r} \leq 1\ and\ uc_k \leq cost\_limit_k \\ ROP_{i,k,r}, else \end{cases} \tag{5}$$

3.2. Stage 2: evaluating the economic benefits of the reviewed SC configuration

Once the spare parts SC configuration has been reviewed (stage 1), an economic evaluation has to be performed to check the achieved cost benefits and verify the importance of reviewing the SC configuration. To this end, stage 2 is carried out, which provides, for the first time, a mathematical model to compare the total cost of the reviewed SC with the one of the starting SC (before the review process). Specifically, the SC total cost is determined using Equation 6 and according to the notation reported in Tables 1-2. Then, the reviewed SC configuration ($r = 1$) is considered economically beneficial in respect with the starting one ($r = 0$) if it has a lower total cost, according to Equation 7.

$$C_{tot_r} = C_{H_r} + C_{O_r} + C_{B_r} + C_{rev_r} \tag{6}$$

$$\begin{cases} if\ C_{tot_1} \leq C_{tot_0} \rightarrow review\ economically\ beneficial \\ else \rightarrow review\ not\ economically\ beneficial \end{cases} \tag{7}$$

Where:

- C_{H_r}, according to Equation 8, depends on the average inventory levels of SKUs in DCs ($AvgInv_{i,k,r}$), which, in turn, depend on $Q'_{i,k,r}$. For this reason, differences between the holding cost in the reviewed SC configuration (C_{H_1}) and the one in the starting SC configuration (C_{H_0}) will only arise concerning those SKUs (($\#SKU_{supply_{i,r}}$) whose supply policy changes during the review ($Q'_{i,k,1} \neq Q'_{i,k,0}$), in response to demand fluctuations ($X_{i,k,1} \neq X_{i,k,0}$).

$$C_{H_r} = \sum_{i=1}^{\#DCs} \sum_{k=1}^{\#SKU} h_{\%} \cdot uc_k \cdot \frac{Q'_{i,k,r}}{2} \tag{8}$$

- C_{O_r}, according to Equation 9, depends on the number of supply orders issued for SKUs in DCs ($\#Ord_{i,k,r}$), which, in turn, depends on the ratio between $X_{r,i,k}$ and $Q'_{i,k,r}$. Like in C_{H_r}, differences between the ordering cost in the reviewed SC configuration (C_{O_1}) and the one in the starting SC configuration (C_{O_0}) will only arise concerning those SKUs, whose supply policy changes during the review ($Q'_{i,k,1} \neq Q'_{i,k,0}$).

$$C_{O_r} = \sum_{i=1}^{\#DCs} \sum_{k=1}^{\#SKU} oc_k \cdot \frac{X_{i,k,r}}{Q'_{i,k,r}} \tag{9}$$

- C_{B_r}, according to Equation 10, depends on the stock-out probabilities allowed in the considered SC configuration based on the desired $SL_{i,k,r}$. Again, differences between the backorder cost in the reviewed SC configuration (C_{B_1}) and the one in the starting SC configuration (C_{B_0}) will only arise concerning those SKUs whose supply policy changes during the review. Indeed, when the demand changes for some SKUs ($X_{i,k,1} \neq X_{i,k,0}$), the reviewed SC configuration updates the related safety stock values (Equation 3) to ensure the desired service level and prevent stock-outs. On the contrary, by not revieweing the SC configuration, the safety stocks are not updated even if the demand increases ($SS_{i,k,1} \neq SS_{i,k,0}$). Therefore, the respective customer service level is lowered ($SL_{i,k,1} \neq SL_{i,k,0}$).

$$C_{B_r} = \sum_{i=1}^{\#DCs} \sum_{k=1}^{\#SKU} uback_k \cdot X_{i,k,r} \cdot (1 - SL_{i,k,r}) \tag{10}$$

- C_{rev_r}, according to Equation 11, is null when the review of the SC configuration is not performed ($r = 0$), while being the sum of three cost items in the opposite case ($r = 1$).

$$C_{rev_r} = \begin{cases} 0 \; if \; r = 0 \\ C_{Sof} + C_{Disp_r} + C_{Adm_r} \; if \; r = 1 \end{cases} \tag{11}$$

Where: C_{Sof} (Equation 12) is a fixed cost, being independent on r; C_{Disp_r} (Equations 13-14) depends on the vehicle used to perform displacements of SKUs; and C_{Adm_r} (Equation 15) can be neglected since tm is very small (on the order of seconds) compared to the period of analysis (on the order of days, months, or even years). It is worth mentioning that C_{Disp_r} is calculated by considering only γ SKUs, since they are the only SKUs for which a displacement has to be made (switching from decentralisation to centralisation). Conversely, α and β SKUs for which a switch is required from centralisation to decentralisation are not considered. Indeed, such SKUs have high/moderate demand and high/moderate turnover rates. Hence, it is not necessary to displace their inventories from the central DC to the decentralised ones, but rather $ROP'_{i,k,r}$ and $Q'_{i,k,r}$ values can be updated in decentralised DCs, while waiting for customers to consume the current stocks in the central DC.

$$C_{Sof} = mh \cdot tc \tag{12}$$

$$C_{Disp_r} = utrip \cdot dist \cdot \#trips_r \tag{13}$$

$$\#trips_r = \frac{\sum_{i=1}^{\#DCs}\sum_{j=1}^{\#\gamma\, SKU_{depl_{i,r}}} X_{i,j,r}*vol_k}{Cap} \tag{14}$$

$$C_{Adm_r} = \sum_{i=1}^{\#DCs} \#SKU_{supply_{i,r}} \cdot tm \cdot mh \tag{15}$$

Two considerations emerge based on the economic evaluation here proposed, which will be demonstrated in the next Section (through two case studies). On the one hand, when performing the first review of a spare parts SC configuration (i.e., the considered company has never performed a SC configuration review before), the review process is expected to be strongly economically convenient, especially if the stock deployment and supply policies have been planned, so far, in an empirical manner (e.g., based on personnel experience). In fact, in the first review, although a large review cost (C_{rev_r}) is expected (since for many SKUs a change in stock deployment and supply policies is attended), C_{rev_r} are likely to be much smaller than the savings achieved by optimising holding, ordering, and backorder costs. Therefore, C_{tot_1} is expected to be lower than C_{tot_0}. On the other hand, after the first review of the SC configuration, in the subsequent reviews a lower C_{rev_r} is expected (since only small adjustments of stock deployment and supply policies will be suggested), but the benefits of aligning stock with the spare parts demand will still be perceived (especially in terms of backorder costs C_{B_r}). Specifically, economic advantages are perceived by performing regular reviews of the spare parts SC configuration since C_{rev_r} is expected to decrease more the more frequently the review is repeated. Indeed, a shorter review interval is associated with fewer fluctuations in the spare parts demand, resulting in lower values of $\#SKU_{supply_{i,r}}$ and $\#\gamma\ SKU_{depl_{i,r}}$.

4. Results and discussion

SP-LACE was applied to two case studies (A and B) with two purposes: first, to test its applicability in real companies. Indeed, by selecting as case studies two spare parts retailers located in different geographical areas, with different territorial expansions, handling different types of spare parts, and serving customers with different features, the general applicability of SP-LACE and its consistency are ensured. Secondly, to check the effectiveness of SP-LACE (also confirming the considerations reported in Section 3.2) by comparing its performance with both the starting (historical) economic performance of the case study companies and the methodology by Stoll et al. (2015).

For applying SP-LACE (and the methodology by Stoll et al. (2015)), the following input data were collected, whose variable names and description have already been provided in Table 1.

1. Input data required to apply **both** SP-LACE and the methodology by Stoll et al. (2015):

a. $SL_{i,k,r}$ desired by the company for each SKU in each DC;

b. Daily inventory withdrawals performed in each DC during the period of analysis (assumed one year), gathering, for each withdrawal, the following information: identifier ($ID\ with_{i,k,r}$) of the specific SKU withdrawn, SKU description, date of withdrawal, identification of the DC where the withdrawal took place, quantity withdrawn to fulfil the received demand;

c. Average uc_k of each SKU (which, due to a non-disclosure agreement, has been here modified, multiplying a coefficient m for each SKU);

d. $X_{i,k,r}$ received in the period of analysis for each SKU in each DC;

e. $LT_{i,k}$ of each SKU in each DC;

f. vol_k of each SKU;

g. $uback_k$ associated with each SKU;

h. oc_k related to each SKU;

i. $h_{\%}$ for keeping stocks in inventory one year;

j. mh;

k. $dist$;

l. Characteristics (Cap and $utrip$) of the vehicle used to perform displacements.

2. Input data required **only** to apply the methodology by Stoll et al. (2015):

a. Evaluation of each SKU in terms of the six VED criticality criteria performed by maintenance experts;

b. Pairwise comparison of the VED evaluations, following the standard procedure of an AHP (Feng et al., 2021).

Moreover, to compare the results of SP-LACE with the historical performance of the case studies, further input data were collected related to the historical daily orders issued by the company to supply each SKU in each DC during the period of analysis. Specifically, for each supply order, the following information was gathered: identifier ($ID\ ord_{i,k,r}$) of the specific SKU ordered, SKU description, date of order issue, identification of the DC where the order took place, and quantity ordered to replenish the DC.

Below, Section 4.1 describes case study A, while Section 4.2 presents case study B.

4.1. Case study A

A bus spare parts retailer from southern Europe was taken as case study A, which manages more than 3,000 SKUs. The company purchases spare parts from a single supplier (official partner of company A), stores the stocks into five DCs ($DC_1 - DC_5$, managed independently without admitting lateral transshipments), and serves both external and internal customers. Indeed, on the one hand, company A offers after-sales services and warranty services to external customers, to whom it sells spare parts for maintenance activities. On the other hand, company A installs spare parts on its internal vehicles, owning a fleet of over 600 buses. In each

DC, the stock deployment and supply policies are selected by warehouse managers, who plan the SC configuration based on experience, without adopting systematic approaches.

In this context, SP-LACE and the methodology by Stoll et al. (2015) were applied to review the SC configuration of company A. In agreement with company A, DC_1 was selected as the central DC, being the facility with the largest size and central location with respect to customers ($dist$ is around 15 km). Furthermore, the input data (mentioned at the beginning of Section 4) were collected, considering as the period of analysis the year 2019. Specifically, $SL_{i,k,r}$ desired for each SKU in each DC was defined by consulting company managers, and they asked it to be 95% for all SKUs. The data related to inventory withdrawals and supply orders carried out in 2019 in each DC were extracted from company databases, as well as the information on uc_k, $X_{i,k,r}$ in 2019, $LT_{i,k}$, oc_k (which resulted in 26.1 €/order for all SKUs), and $h_{\%}$ (which resulted in 9.87% according to a company evaluation). Concerning $LT_{i,k}$, based on the contract between company A and its supplier, the procurement lead time depends only on the DC (i) and not on the SKU (k), being equal to 10 days for SKUs stored in DC_2, DC_3 and DC_5, while being 4 days for SKUs in DC_1 and DC_4. In addition to this data, to apply only the methodology by Stoll et al. (2015), ten meetings were organised with a panel of company maintenance experts (each lasting approximately four hours), where they were asked to evaluate SKUs according to the VED criticality criteria, then performing the AHP.

The results achieved by reviewing the SC configuration through the stage 1 of SP-LACE and the methodology by Stoll et al. (2015) are expressed in Table 3, reporting, for a sample of ten SKUs in DC_2, the suggested criticality classification ($CrC_{i,k,r}$), stock deployment policies ($DP_{i,k,r}$), and stock supply policies ($SP_{i,k,r}$), where the latter are calculated with Equations 4-5 ($ROP'_{i,k,r}, Q'_{i,k,r}$) in the case of SP-LACE, while being calculated with Equations 1-2 ($ROP_{i,k,r}, Q_{i,k,r}$) in the methodology by Stoll et al. (2015). In addition to this information, Table 3 reports the identifier (ID_k) and description of each SKU, its total demand ($X_{i,k,r}$) in 2019 in DC_2, the unitary cost (uc_k), the coefficient of variation of demand ($\theta\left(x_{i,k,r}\right)$), and the number of supply orders ($\#Ord_{i,k,r}$) issued in 2019 in DC_2.

Table 3. Comparison of the criticality classification (CrC), stock deployment policies (DP), and supply policies (SP) suggested by the stage 1 of SP-LACE and the literature metodology (literat., (Stoll et al., 2015)) for a sample of ten SKUs in DC_2 (i=2). The symbol "-" suggests to keep no stock for the considered SKU (on-demand supply).

ID_k and description	$X_{2,k,r}$	uc_k	$\theta(x_{2,k,r})$	$\#Ord_{2,k,r}$ issued historically	$CrC_{2,k,r}$ literat.	$CrC_{2,k,r}$ SP-LACE	$DP_{2,k,r}$ literat.	$DP_{2,k,r}$ SP-LACE	$SP_{2,k,r}$ literat. $(ROP_{2,k,r}, Q_{2,k,r})$	$SP_{2,k,r}$ SP-LACE $(ROP'_{2,k,r}, Q'_{2,k,r})$
415684 splashback	44	72.9	8.1	22	HZV	HX → α	Decentralisation of 1 unit	Decentralisation according to (ROP', Q')	(0,1)	(6,14)
102546 1-pole socket	96	29.5	5.7	13	LZV	LX → β	Decentralisation according to (ROP, Q)	Decentralisation according to (ROP', Q')	(10,41)	(10,41)
100278 diesel filter	56	65.6	1.8	54	MYV	MX → α	Decentralisation of 1 unit and centralisation in DC_1 according to (ROP, Q)	Decentralisation according to (ROP', Q')	(0,1)	(7,20)
100327 damper repair kit	31	366.1	2.2	30	HYV	HX → α	Centralisation in DC_1 according to (ROP, Q)	Decentralisation according to (ROP', Q')	-	(3,5)
100998 brake cylinder connection	47	34.4	23.6	6	LZV	LX → β	Decentralisation according to (ROP, Q)	Decentralisation according to (ROP', Q')	(3,11)	(3,11)
851302 front-right fog lamp	1	160.3	0	1	HXD	HY → α	No stock	No stock	-	-
415846 left seat rivet	1	213.3	0	1	HXE	HY → α	Centralisation of 1 unit in DC_1	No stock	-	-
729813 curtain fastener	19	31.0	16.1	5	LZV	LX → β	Decentralisation according to (ROP, Q)	Decentralisation according to (ROP', Q')	(4,17)	(4,17)
7184090 front hub cover	1	26.0	0	0	LXD	LY → γ	No stock	Centralisation in DC_1 according to (ROP', Q')	-	-
944134 water filter	5	48.4	36.5	4	MZV	MX → α	Decentralisation of 1 unit	Decentralisation according to (ROP', Q')	(0,1)	(3,7)

Table 3 shows that SP-LACE leads to a different criticality classifications (CrC) of spare parts than the methodology by Stoll et al. (2015), resulting in the same stock deployment and supply policies only for four out of ten SKUs. Regarding the stock deployment policies, SP-LACE keeps all SKUs decentralised except one, promoting decentralisation for more SKUs than Stoll et al. (2015). Concerning the stock supply policies, SP-LACE favours higher reorder levels and optimal order quantities, preferring large supply batches and sporadic supply orders, while the methodology by Stoll et al. (2015) often recommends the opposite (one-unit lots and frequent supply orders). The aforementioned considerations are confirmed in Figure 3, which provides an aggregated view of the results obtained for all SKUs (not just a sample of ten) in all DCs (not only DC_2), comparing the performance of SP-LACE (orange), the methodology by Stoll et al. (2015) (blue), and the historical situation of company A in 2019 (grey).

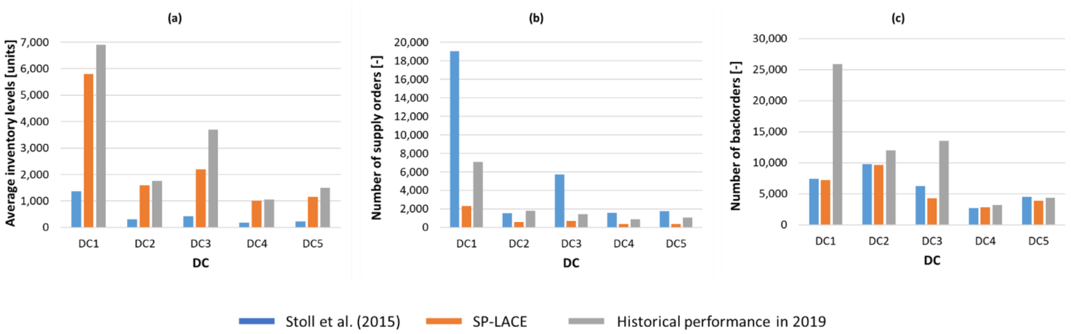

Figure 3. Total average inventory levels (a), number of orders (b), and number of backorders (c) occurred in each DC historically in 2019 (grey), by applying the stage 1 of SP-LACE (orange), and the methodology by Stoll et al. (2015) (blue), respectively.

Specifically, Figure 3.a shows the sum of the average inventory levels ($AvgInv_{i,k,r}$) of all SKUs in each DC, highlighting that SP-LACE decentralises stocks more than the methodology by Stoll et al. (2015). Indeed, by comparing the orange and blue histograms of Figure 3.a, it appears that the methodology by Stoll et al. (2015) stores 55% of the total stocks in the central DC, while holding only small amounts of spare parts in peripheral DCs (12% in DC_2, 17% in DC_3, 7% in DC_4, and 9% in DC_5). Instead, SP-LACE centralises fewer spare parts (47% of the total stocks are in DC_1), while holding in the other DCs 14%, 19%, 9%, and 11% of stocks, respectively. Moreover, Figure 3.a illustrates that, in terms of average inventory levels, both SP-LACE and the methodology by Stoll et al. (2015) perform better than the historical situation of company A, showing that the review of the SC configuration reduces the DCs' filling. However, SP-LACE results in higher average inventory levels than the methodology by Stoll et al. (2015), due to a stronger tendency to decentralisation and the adoption of higher reorder levels and optimal order quantities for many SKUs. Concurrently, Figure 3.b depicts the sum of the number of supply orders ($\#Ord_{i,k,r}$) issued for all SKUs in each DC, highlighting that SP-LACE strongly reduces the number of supply orders by suggesting large replenishment batches and sporadic supply orders. On the contrary, the methodology by Stoll et al. (2015) worsens the historical situation by recommending frequent supplies of one-unit lots. Finally, Figure 3.c reports the sum of the number of annual backorders that occurred for all SKUs in each DC. Taking into account Figure 3.c, it appears that both SP-LACE and the methodology by Stoll et al. (2015) reduce the number of backorders with respect to the historical situation of company A. However, SP-LACE achieves fewer backorders since it is a data-driven methodology. Indeed, SP-LACE classifies the criticality of SKUs based on the analysis of objective data (not on the consultation of maintenance experts). Therefore, no subjectivity affects the criticality classification results, and mistakes are avoided (unlike in the methodology by Stoll et al. (2015)), in which critical SKUs are identified as non-critical, suggesting to keep few items in stock. Finally, by keeping higher inventory levels (instead of one-unit lots), SP-LACE makes the stocks in DCs more resilient compared to the methodology by Stoll et al. (2015). Indeed, SP-LACE allows company A to better cope with unexpected demand fluctuations (typical of spare parts) preventing future stock-outs and backorder costs in case of demand variations.

The economic impact of reviewing the SC configuration of company A was, then, evaluated (in terms of SC total costs - C_{tot_r}, Equation 6) following the stage 2 of SP-LACE. Hence, the economic performance of the reviewed SC configuration ($r = 1$) was compared with the starting (historical) one ($r = 0$). Figure 4 depicts the achieved results in terms of holding (C_{H_r}, Equation 8), ordering (C_{O_r}, Equation 9), and backorder costs (C_{B_r}, Equation 10), which are expressed in Euros (€) and obtained by applying SP-LACE, the methodology by Stoll et al. (2015), and the historical company performance (starting SC configuration), respectively. Moreover, Figure 4 shows the cost incurred to review the SC configuration (C_{rev_r}, Equation 11), where trucks with a capacity of 13 m^3 (Cap) and a cost of 0.6 €/km ($utrip$) were considered to perform spare parts displacements. To show the benefits of a regular review of the SC configuration in company A, the review of the SC configuration was not carried out only once, but twice. Indeed, as shown in Figure 4.a, a first review was conducted to move from the starting (historical) SC configuration to a reviewed one, which was more aligned with the spare parts demand of 2019. Then, as depicted in Figure 4.b, after one year, a second review was performed by repeating the application of SP-LACE in 2020 and moving to another SC configuration aligned with the demand of 2020. Both Figures (4.a and 4.b) depict the economic evaluation of the reviewed SC configuration ($r = 1$, in 2019 and 2020, respectively), comparing it with the economic performance that company A would have had by not reviewing the SC configuration (i.e., maintaining the starting SC configuration, $r = 0$).

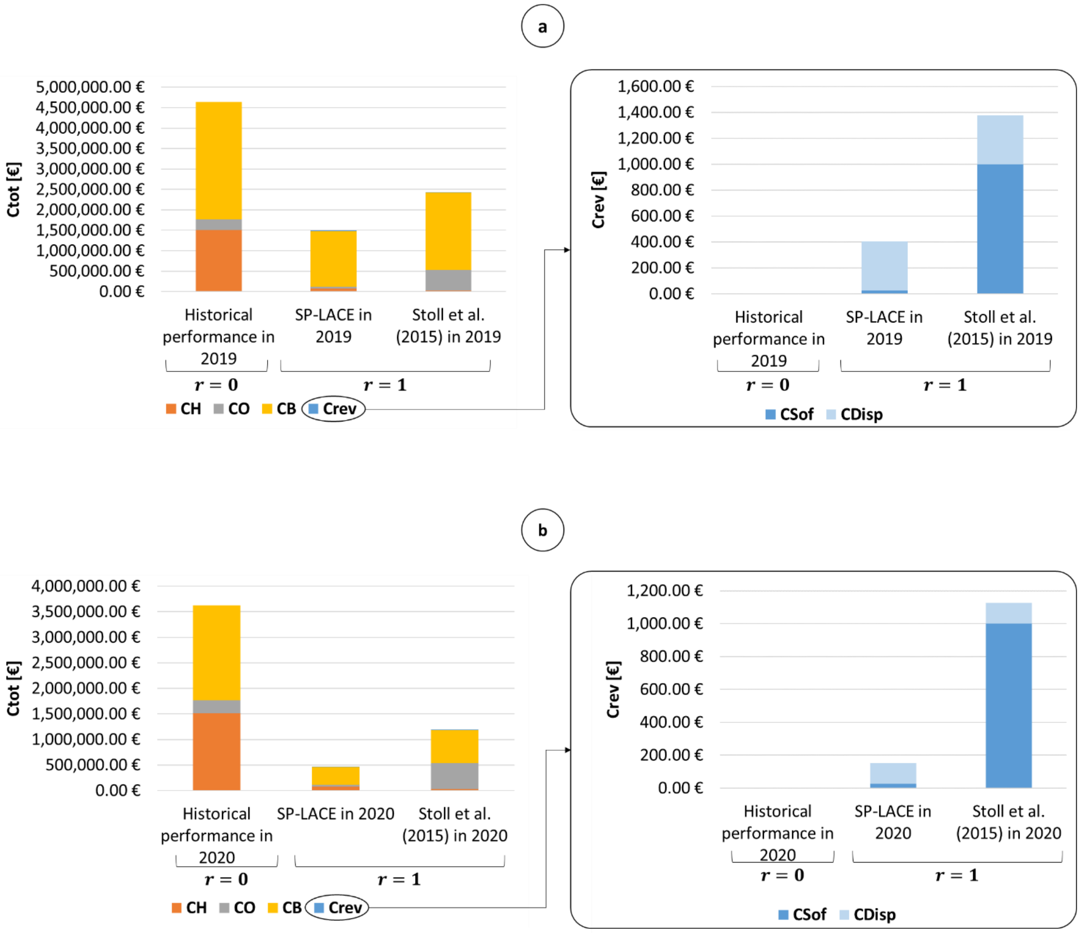

Figure 4. Economic assessment of SC total cost (Ctot) achieved without performing SC configuration reviews (r=0) or by performing a first (a, in 2019) and a second (b, in 2020) review (r=1) through SP-LACE and the methodology by Stoll et al. (2015), respectively.

Figure 4 proves that both the first (Figure 4.a) and the second (Figure 4.b) review ($r = 1$) of the SC configuration were economically convenient for company A in respect with keeping the starting SC configuration unchanged over time ($r = 0$). Indeed, company A had never performed a structured SC configuration review before 2019. Therefore, major holding, ordering, and backorder cost savings were achieved by aligning the SC configuration with spare parts demand, leading to a drastic reduction in C_{tot_r} with both SP-LACE and the methodology by Stoll et al. (2015). Specifically, SP-LACE appeared more economically advantageous, resulting in a lower SC total cost compared with both Stoll et al. (2015) (-39% in 2019 and -61% in 2020) and the historical situation (-68% in 2019 and -87% in 2020). Indeed, Figure 4 shows that, in both the reviews, SP-LACE determined less ordering and backorder costs than the methodology by Stoll et al. (2015), while implying higher holding costs. Lower ordering costs and higher holding costs were obtained since SP-LACE prefers larger supply batches and sporadic supply orders compared with the methodology by Stoll et al. (2015). Instead, lower backorder costs were obtained since SP-LACE is a data-driven methodology, which classifies the criticality of SKUs based on objective input data. On the contrary, the methodology by Stoll et al. (2015) implies consulting maintenance experts, and this leads to SC configuration reviews affected by subjectivity, causing backorders when critical SKUs are wrongly classified as moderately criticals or non criticals, suggesting for them wrong stock deployment and supply policies. Finally, Figure 4 shows that reviewing the SC configuration implied incurring in a review cost (C_{rev_r}), which was higher in the first review of the SC configuration (since the stock deployment and supply policies of 99.2% of SKUs were changed), while being lower in the second one (since only small adjustments of stock deployment and supply policies were suggested, updating the management of 31% of SKUs). Specifically, C_{rev_r} was lower in SP-LACE than in the methodology by Stoll et al. (2015) and this economic benefit was mainly related to the time consumption (C_{Sof_r}) required to collect the input data and perform the SC configuration review. In fact, in SP-LACE the input data related to the 3,000 SKUs was collected by executing a single search query on company databases, which provided results in less than an hour. Consequently, the reviewed SC configuration was achieved in one hour (tc), leading to a review cost equal to 403 € in the first review of the SC configuration and 151 € in the second one. In contrast, the collection of input data for the methodology by Stoll et al. (2015) not only required to perform the same search query in the company databases, but also to consult maintenance experts for developing the VED analysis and the AHP. This, as aforementioned, involved organising ten meetings of around four hours each, obtaining the results of stock deployment and supply policies only after forty working hours, and leading to a review cost of 1,378 € in the first review and 1,126 € in the second one. The lower time consumption of SP-LACE resulted in a greater applicability of this methodology in company A, encouraging regular reviews of spare parts SC configurations.

4.2. Case study B

A spare parts retailer from northern Europe was selected as case study B, which manages almost 8,000 SKUs falling into three categories: spare parts for trams (24% out of the total 8,000 SKUs), spare parts for subways (64%), and spare parts for repairing or replacing railway and subway infrastructure (the remaining 12%). The company purchases spare parts from several suppliers, stocking them into eight DCs ($DC_1 - DC_8$) based on the experience of warehouse staff. Finally, spare parts are installed on company's internal vehicles or infrastructures.

Both SP-LACE and the methodology by Stoll et al. (2015) were applied in company B, where the input data mentioned at the beginning of Section 4 were gathered as follows. The required $SL_{i,k,r}$ for each SKU in each DC was defined by consulting company managers. As in case study A, it was requested to be 95% for all SKUs. Then, considering as period of analysis the year 2021, the data related to inventory withdrawals and supply orders carried out in 2021 in each DC were extracted from company databases, as well as the information on uc_k, $X_{i,k,r}$ in 2021, $LT_{i,k}$, oc_k (which resulted in 5 €/order for all SKUs), and $h_{\%}$ (which resulted in 10% according to a company evaluation). In addition to these data, to apply the methodology by Stoll et al. (2015), fifteen online meetings (each lasting three hours) were organised, where a panel of maintenance experts was asked to evaluate SKUs according to the VED criticality criteria, then performing the AHP.

However, it is worth mentioning three aspects that distinguish data extraction and SP-LACE application in case study B from case study A. First, in case study B, a specific average procurement lead time ($LT_{i,k}$) was collected for each individual SKU (k) in each DC (i), not being the same for all SKUs, but varying according to the suppliers, DCs, and the specific SKU ordered. Second, in case study B, the DC chosen as central DC varies depending on the spare parts typology (while, in case study A, a single central DC - DC_1 - was identified for the SC configuration related to all SKUs). In particular, company B asked to impose DC_6 as the central DC for the management of tram SKUs, DC_1 for subways SKUs, and DC_2 for infrastructure SKUs. Finally, in terms of the daily quantities withdrawn from DCs, lateral transshipments were allowed and treated according to Appendix A. Below, the case study results are shown. Table 4 compares the criticality classification ($CrC_{i,k,r}$), the stock deployment policies ($DP_{i,k,r}$), and the stock supply policies ($SP_{i,k,r}$) suggested by the stage 1 of SP-LACE and the methodology by Stoll et al. (2015) for a sample of ten SKUs in DC_1, reporting the average procurement lead time ($LT_{i,k}$, expressed in days) and the SKUs' typology together with the same information already discussed in Table 3.

Table 4. Comparison of the criticality classification (CrC), stock deployment policies (DP), and supply policies (SP) suggested by the stage 1 of SP-LACE and the literature metodology (literat., (Stoll et al., 2015)) for a sample of ten SKUs in DC_1 (i=1). The symbol "-" suggests to keep no stock for the considered SKU (on-demand supply).

ID_k and description	$X_{1,k,r}$	uc_k	$\theta(x_{1,k,r})$	$\#Ord_{i,k},r$	$LT_{1,k}$	$CrC_{1,k,r}$ literat.	$CrC_{1,k,r}$ SP-LACE	$DP_{1,k,r}$ literat.	$DP_{1,k,r}$ SP-LACE	$SP_{2,k,r}$ literat. $(ROP_{1,k,r}, Q_{1,k,r})$	$SP_{2,k,r}$ SP-LACE $(ROP'_{1,k,r}, Q'_{1,k,r})$
821302 tie rod (tram SKU)	88	155.1	7.1	18	70	MZV	MX → α	Decentralisation of 1 unit	Decentralisation according to (ROP', Q')	(0,1)	(20,8)
211405 driver seat (tram SKU)	5	1,816.5	84.1	3	8	HZV	HY → α	Decentralisation of 1 unit	Decentralisation according to (ROP', Q')	(0,1)	(3,1)
603059 group selector (infrastructure SKU)	9	4.4	70.1	1	1	LZD	LY → γ	Decentralisation of 1 unit	Centralisation in DC_2 according to (ROP', Q')	(0,1)	-
400006 video receiver unit (subway SKU)	67	4,077.3	1.4	60	79	HXV	HX → α	Centralisation of 1 unit in DC_1	Decentralisation according to (ROP', Q')	(0,1)	(33,1)
400007 brake control unit (subway SKU)	42	5,858.8	1.7	40	57	HYV	HX → α	Decentralisation of 1 unit and centralisation in DC_1 according to (ROP, Q)	Decentralisation according to (ROP', Q')	(20,1)	(19,1)
241104 sealing ring (tram SKU)	14	48.8	35.5	6	80	LZV	LX → β	Decentralisation according to (ROP, Q)	Decentralisation according to (ROP', Q')	(11,6)	(11,6)
400001 thread lock (subway SKU)	22	146.6	13.1	10	12	LZV	LX → β	Decentralisation according to (ROP, Q)	Decentralisation according to (ROP', Q')	(4,3)	(4,3)
400018 wheel axle (subway SKU)	3	3,206.4	0	1	90	HXV	HZ → β	Centralisation of 1 unit in DC_1	No stock	(0,1)	-
498913 coupling between gear and engine (subway SKU)	2	2,873.9	0	1	210	HXV	HZ → β	Centralisation of 1 unit in DC_1	No stock	(0,1)	-
215112 fire extinguisher (infrastructure SKU)	370	47.4	13.9	14	17	HZV	HX → α	Decentralisation of 1 unit	Decentralisation according to (ROP', Q')	(0,1)	(41,28)

Table 4 confirms the considerations already reported for case study A (Table 3), showing that only for two out of ten SKUs SP-LACE suggested the same stock deployment and supply policies than the methodology by Stoll et al. (2015). In the remaining cases, concerning stock deployment policies, SP-LACE preferred decentralisation for a higher number of SKUs. On the other hand, concerning stock supply policies, a visible inclination of SP-LACE towards more sporadic and voluminous reordering batches was seen, while the methodology by Stoll et al. (2015) preferred one-unit lots. In addition, Table 4 proves the importance of considering not only normal demand distributions, but also Poisson distributions for spare parts, thus validating SP-LACE results. Indeed, all SKUs except 821302 and 215112 showed an average demand during the procurement lead time lower than 15 units, demonstrating that not all SKUs have a normally distributed demand, but rather some of them follow a Poisson distribution. Therefore, the coefficient of variation of demand ($\theta\left(x_{1,k,r}\right)$) is not an adequate parameter to delineate the SKUs' criticality, while it is preferable to rely on $\#Ord_{i,k,r}$.

Like in case study A, the aforementioned considerations were confirmed in Figure 5, showing that similar results of criticality classification ($CrC_{i,k,r}$), stock deployment ($DP_{i,k,r}$), and supply policies ($SP_{i,k,r}$) were obtained in the other DCs (not only in DC_1) and considering all SKUs (not just a sample). Figure 5 depicts, for each DC and for each SKUs typology (tram, subway, and infrastructure SKUs), the same information already described in Figure 3, comparing SP-LACE (orange), the methodology by Stoll et al. (2015) (blue), and the historical performance of company B in 2021 (grey).

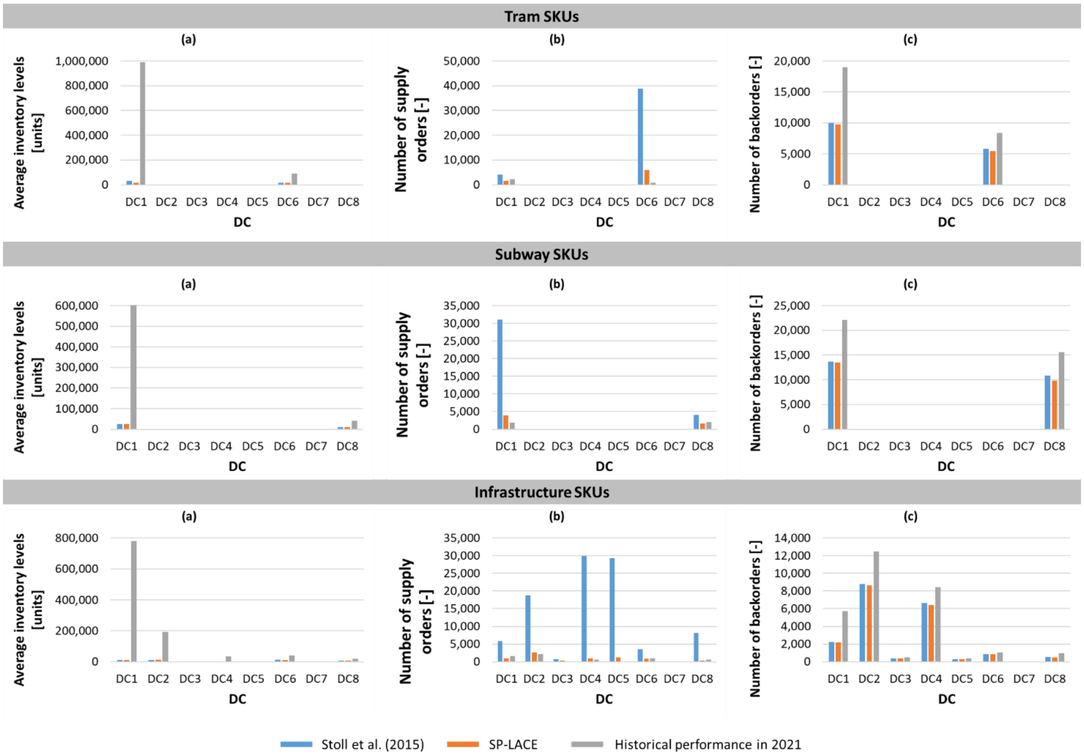

Figure 5. Total average inventory levels (a), number of orders (b), and number of backorders (c) occurred in each DC historically in 2021 (grey), by applying the stage 1 of SP-LACE (orange), or the methodology by Stoll et al. (2015) (blue), and considering tram (top), subway (middle), and infrastructure (bottom) SKUs.

Figure 5 shows the importance of adopting a structured methodology to review the configuration of spare parts SCs. Indeed, by reviewing the SC configuration, company B achieved a significant decrease in the average inventory levels, number of supply orders, and number of backorders, improving the economic investments in resources both with SP-LACE and the methodology by Stoll et al. (2015). Furthermore, Figure 5 confirms the results of case study A (Figure 3), showing that the stock deployment and supply policies suggested by SP-LACE, despite leading to higher inventory levels (Figure 3.a), determined a drastic reduction in the number of supply orders (Figure 3.b) due to higher values of reorder levels and optimal order quantities. Conversely, in terms of supply orders, the methodology by Stoll et al. (2015) worsen the historical situation. Finally, a reduction in the number of backorders (Figure 3.c) was achieved in SP-LACE, not only improving the company's historical situation but also showing advantages over the methodology by Stoll et al. (2015) since a data-driven criticality classification of SKUs was performed. Whereas, due to the consultation of maintenance experts, the methodology by Stoll et al. (2015) produced subjective results of SC configuration review, sometimes associating SKUs with the wrong criticality class and adopting unoptimal stock deployment and supply policies.

Like in case study A, the economic impact of the stage 1 of SP-LACE on company B was evaluated in terms of SC total costs (C_{tot_r}, Equation 6). To this end, the stage 2 of SP-LACE was applied, comparing holding (C_{H_r}, Equation 8), ordering (C_{O_r}, Equation 9), backorder (C_{B_r}, Equation 10), and review costs (C_{rev_r}, Equation 11) of the reviewed SC configuration ($r = 1$) with the ones of the starting (historical) SC configuration ($r = 0$). Figure 6 depicts the results achieved through SP-LACE, the methodology by Stoll et al. (2015), and the historical company performance in 2021, respectively. Since the SC configuration review was performed at the same time for tram, subway, and infrastructure SKUs (applying SP-LACE to all SKUs), the cost values in Figure 6 are shown in an aggregated form. C_{rev_r} was calculated by considering (for the displacement of SKUs) vehicles with a capacity of 16 m^3 (Cap) and a cost of 0.7 €/km ($utrip$).

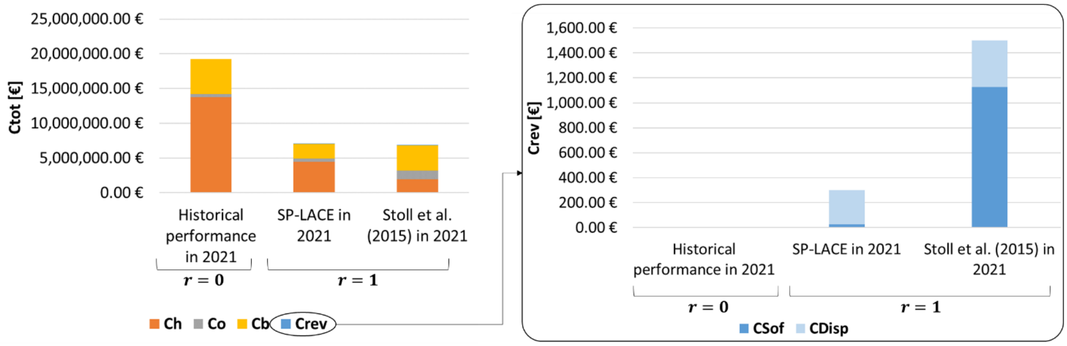

Figure 6. Economic assessment of SC total cost (Ctot) achieved historically (in 2021, without performing reviews of the SC, r=0) or by reviewing the SC configuration (r=1) through SP-LACE and the methodology by Stoll et al. (2015), respectively.

Figure 6 shows that reviewing the SC configuration was economically convenient for company B in respect with the starting SC configuration. Indeed, a reduction in C_{tot_r} was achieved both with SP-LACE and the methodology by Stoll et al. (2015). Like in case study A, SP-LACE determined less ordering and backorder costs than Stoll et al. (2015), while implying higher holding costs. However, in case study B, contrarily to case study A, SP-LACE led to a higher SC total cost (+3%) than the methodology by Stoll et al. (2015) and this result was due to the reduced cost of issuing one supply order in company B ($oc_k = 5$ €$/order$, different from 26.10 €/order of company A). In fact, given the reduced value of oc_k, the small number of supply orders achieved in SP-LACE (Figure 5) does not compensate for the increase in holding costs compared to the methodology by Stoll et al. (2015). However, it is worth mentioning that SP-LACE would have become cost-effective compared to Stoll et al. 2015 if the cost of issuing an order would have been 6 €/order (instead of 5 €/order), downplaying the advantage of the methodology by Stoll et al. (2015) over SP-LACE. Moreover, SP-LACE still conserves strong advantages in terms of time-savings and review cost. Indeed, only one search query was performed in company databases, collecting the input data related to 8,000 SKUs and applying SP-LACE in approximately one hour (tc) with a C_{rev_r} of 300 €. Instead, in the methodology by Stoll et al. (2015), besides consulting company databases, fifteen meetings were required to consult maintenance experts and conduct the VED analysis and the AHP, thus obtaining the input data and the results of stock deployment and supply policy in fortyfive working hours (with a C_{rev_r} of 1,499 €). Based on this, despite the higher total cost, SP-LACE appeared more applicable in real companies than the methodology by Stoll et al. (2015), being less time-consuming and allowing regular reviews of the spare parts SC configuration. Moreover, not needing to consult company maintenance experts and requiring less input data (usually available in company databases), SP-LACE showed not only higher applicability in real companies, but also higher reliability than the methodology by Stoll et al. (2015) providing results not affected by subjectivity and reducing backorder costs.

Since, the review of the SC configuration was only performed once in company B (in 2021), a second review of the SC configuration will be performed at the end of 2022 to further confirm the previous considerations and the importance of reviewing the SC configuration.

5. Conclusions

This paper proposes the novel SP-LACE methodology to review the configuration of spare parts SCs based on a multi-criteria criticality classification. In fact, regularly reviewing the SC configuration is important for spare parts retailers to align stock deployment and supply policies with customer needs. Furthermore, the use of a multi-criteria ABC criticality classification to review the SC configuration is reported to be beneficial, allowing spare parts retailers to quickly and easily handle thousands of SKUs simultaneously, and establishing for each of them the most appropriate stock deployment and supply policies. However, the literature is lacking in this perspective since only one methodology (Stoll et al., 2015) based on a multi-criteria ABC criticality classification has been proposed, which presents some limitations, being not applicable in real companies: it requires collecting input data hardly available in real companies and consulting company experts. Therefore, it is subjective and time-consuming, preventing regular reviews of the SC configuration. In addition, it represents the demand for spare parts with a normal distribution, although the demand for spare parts often follows a Poisson distribution. Finally, it does not provide any economic analysis of the cost benefits achievable by reviewing the configuration of spare parts SC, thus missing a demonstration of its effectiveness. Due to these limitations, companies are currently lacking a reliable and applicable methodology to regularly review the spare parts SC configuration based on a multi-criteria ABC criticality classification. To fill this gap, as the main contribution of this work, SP-LACE was developed to overcome the identified drawbacks and provide spare parts retailers with a quick, repeatable, and data-driven methodology to review the configuration of spare parts SCs. In SP-LACE, two stages are carried out. In stage 1, the optimal stock deployment and supply policies are suggested for each SKU, searching (through a multi-criteria criticality classification) for a trade-off between holding, ordering, and backorder costs in DCs. In stage 2, a mathematical model is proposed to evaluate the economic benefits of the reviewed SC configuration (in terms of SC total costs) in respect with the starting one (before the review process).

To test and validate SP-LACE, it was applied to two case studies. The achieved results were compared (in terms of average inventory levels, number of supply orders, number of backorders, holding, ordering, backorder, and review costs) with the historical company performance (starting SC configuration) and also with the methodology by Stoll et al. (2015). The two case studies proved the importance of adopting a structured methodology to regularly review the configuration of spare parts SCs. In fact, SP-LACE significantly improved the starting (historical) economic situation of companies, indicating that the stock deployment and supply policies associated so far with SKUs were not aligned with customer needs. Moreover, the results of the two case studies highlighted the advantages of SP-LACE over the methodology by Stoll et al. (2015), proving that SP-LACE leads to lower ordering and backorder costs, reducing the SC total cost despite higher holding costs (especially when the unitary cost of issuing one supply order - oc_k - is high or the unitary cost of inventory - $h_{\%}$ - is low). These advantages are achieved since SP-LACE decentralises stocks more than the methodology by Stoll et al. (2015), also suggesting the replenishment of DCs through large batches and sporadic supply orders. Moreover, SP-LACE showed great time savings than the methodology by Stoll et al. (2015) and higher applicability in companies with thousands of SKUs and variable spare parts demand since only one hour and lower review costs (C_{rev_r}) were needed to produce objective results, allowing the regular review of SCs configuration and ensuring the desired service level.

Since SP-LACE has been demonstrated to be easily and quickly applicable, this paper allows for the first time adopting (in real companies) a multi-criteria ABC criticality classification of spare parts not only as a technique for planning the stock supply policies in a single DC, but also for planning stock deployment policies in multiple DCs. Moreover, this paper shows, for the first time, the economic benefits of regularly reviewing a spare parts SC configuration. Hence, this work could encourage spare parts retailers to update their starting SC configuration, leading to greater customer satisfaction (due to a better ability to follow demand fluctuations), as well as reduced SC total costs.

The authors envision two future developments of this study: first, to remove some simplifying assumptions of SP-LACE, for example including in the investigation the transportation costs, which are not considered here. Second, to determine (based on the economic evaluation herein provided) the optimal time interval for reviewing the SC configuration, finding a trade-off between review costs and holding, ordering, and backorder costs.

Appendix A

Lateral transshipments are usually performed when the stocks in a DC are not sufficient to meet the customer needs, so it is necessary to procure stocks from another DC (Cohen et al., 1988). Considering as an example two DCs (DC_1 and DC_2), if DC_1 receives a demand for spare parts but it is unable to satisfy it, it can order the required stocks from DC_2. Consequently, the stocks are first withdrawn from DC_2 (first type of withdrawal, that is the lateral transshipment) and delivered to DC_1 to satisfy its request. Then, the stocks are withdrawn from DC_1 (second type of withdrawal) to satisfy the customer need. Based on this, in this work, we have considered as withdrawals (spare parts demand) only the second type of withdrawals, while the lateral transshipments (first type of withdrawal) are not considered for the following reason. In the first instance, it is reasonable to assume that, by applying SP-LACE in each DC, the suggested stock deployment and supply policies and the consequent inventory levels (calculated to compensate both ordinary demands and the demands related to the second type of withdrawals) are sufficient to meet the needs of local customers (Tapia-Ubeda et al., 2020). Subsequently, since SP-LACE can be applied more than one time, by recursively reviewing the spare parts SC configuration, a better alignment of stocks with customer needs is expected in the company's future and, in a long-term evaluation, it is reasonable to expect a reduction or even the removal of lateral transshipments.

Data availability statement

The authors confirm that the data supporting the findings of this study are available within the article [and/or] its supplementary material.

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International Journal of Production Research

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/tprs20

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To cite this article: Alessandra Cantini, Mirco Peron, Filippo De Carlo & Fabio Sgarbossa (2022): A decision support system for configuring spare parts supply chains considering different manufacturing technologies, International Journal of Production Research, DOI: 10.1080/00207543.2022.2041757

To link to this article: https://doi.org/10.1080/00207543.2022.2041757

INTERNATIONAL JOURNAL OF PRODUCTION RESEARCH
https://doi.org/10.1080/00207543.2022.2041757

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A decision support system for configuring spare parts supply chains considering different manufacturing technologies

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ABSTRACT
A well-configured spare parts supply chain (SC) can reduce costs and increase the competitiveness of spare parts retailers. A structured method for configuring spare parts SCs should be used to determine whether to centralise or decentralise inventory management, also considering hybrid configurations. Moreover, such a method should define whether or not to switch the production of spare parts from Conventional Manufacturing (CM) technologies to Additive Manufacturing (AM) ones. Indeed, AM is considered the next revolution in the field of spare parts, and the adoption of AM technologies strongly affects the characteristics of SCs. However, the choice between centralisation and decentralisation is not the subject of much scientific research, and it is also not clear when AM would be the preferable manufacturing technology for spare parts. This paper aims to assist managers and practitioners in determining how to design their spare parts SCs, thus defining both the spare parts SC configuration and the manufacturing technology to adopt through the development of a decision support system (DSS). The proposed DSS is a user-friendly decision tree, and, for the first time, it allows comparison of the total costs of SCs characterised by different degrees of centralisation with both AM and CM spare parts.

ARTICLE HISTORY
Received 20 October 2021
Accepted 3 February 2022

KEYWORDS
Spare parts logistics; supply chain configuration; additive manufacturing (AM); decision tree; decision support system (DSS)

1. Introduction

Over the last decade, factors like globalisation, competition, reduced time-to-market, and high productivity have made the impact of logistics on supply chain (SC) profits greater than in the past (Dominguez, Cannella, and Framinan 2021). Consequently, researchers have started investigating how to improve logistics activities, and acting on the SC configuration has proved to be an effective way to do so. However, changes in the SC configuration profoundly influence not only the logistics activities, but also other aspects such as capital investments (Jiang and Nee 2013), sustainability (Tsao et al. 2021), and customer service (Fathi et al. 2021). For this reason, optimising the SC configuration represents a challenging task (Vlajic, Van Der Vorst, and Haijema 2012).

When dealing with spare parts, it becomes even more challenging to optimise the SC configuration. In fact, in spare parts SCs, a high customer service level is required as the effects of inventory stock-outs on spare parts SC performance can be financially significant (Stoll et al. 2015; Tapia-Ubeda et al. 2020). Hence, a customer-centred perspective should be adopted (Giannikas, McFarlane, and Strachan 2019), and spare parts retailers should configure their SCs to locate distribution centres (DCs) close to the end customers and align stocks to meet their demand (a.k.a. decentralised SC configuration) (Cohen, Agrawal, and Agrawal 2006). Decentralisation usually ensures a rapid response to demand, fast deliveries (which result in reduced maintenance time), low transportation costs, and high flexibility (Alvarez and van der Heijden 2014). However, the demand for spare parts is usually unpredictable, sporadic, and slow-moving (Van der Auweraer and Boute 2019). Therefore, having many decentralised DCs and expecting to guarantee a high service level implies keeping a large amount of stock, thus experiencing high holding costs and reduced inventory turnover. In this sense, adopting a centralised SC configuration with a single warehouse that serves the entire customer population could help benefit from the risk-pooling effect (Milewski 2020). A single DC will be more profitable than several DCs also in terms of facility costs (e.g. lighting and heating) (Wanke and Saliby 2009).

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Supplemental data for this article can be accessed here. https://doi.org/10.1080/00207543.2022.2041757

However, a centralised SC configuration loses the benefits of the rapid response to demand, fast deliveries, and low transportation costs of decentralised SCs. According to Cavalieri et al. (2008), the advantages of the two basic SC configurations (centralisation and decentralisation) could be balanced by building hybrid SCs, where spare parts are stocked at different holding points, and the number of DCs serving customers represents an intermediate solution between centralisation and decentralisation. Given the wide range of possible configurations and the contrasting advantages of different degrees of centralisation, it is becoming both a strategic opportunity and a challenge to find methodologies for configuring optimal spare parts SCs. In this perspective, as stated by Avventuroso et al. (2018) and Khajavi, Partanen, and Holmström (2014), a cost–benefit analysis should be performed to identify a solution that ensures high-quality responses to customers and improved asset utilisation while reducing expenses.

As stated by Milewski (2020) and Tapia-Ubeda et al. (2020), although it has been known for a long time that efficient spare parts SC configuration strongly impacts the SC's economy, the choice between centralisation and decentralisation is still overlooked in the literature. As better described in Section 2, in fact, many scientific studies focus on topics such as optimising inventory control policies in a single DC, maximising the performance of a specific SC configuration (that is initially chosen and not compared with others), or performing qualitative comparisons between SC configurations, but quantitative methods to compare different SC configurations are not yet the subject of much scientific research. As things stand today, many spare parts retailers are hence far from a proper implementation of structured methods to optimise their SC configurations and the choice between centralisation and decentralisation continues to be arbitrary and based on experience. In this context, a quick and easy-to-use tool that supports managers and practitioners in optimising spare parts SC configurations is highly claimed (Cohen, Agrawal, and Agrawal 2006; Graves and Willems 2005). This work aims to address this need by developing a decision support system (DSS) that will answer the following research question:

> **RQ1)** Under which conditions is it economically profitable to have a centralised, decentralised, or hybrid spare parts SC configuration?

In addition to this, the world of spare parts has recently investigated the possibility of producing spare parts via Additive Manufacturing (AM), since this technology offers the opportunity to fundamentally revolutionise spare parts SC configurations (Heinen and Hoberg 2019). Indeed, AM allows the production of spare parts on-demand, thus enabling the configuration of spare parts SCs with no inventories (Knofius, van der Heijden, and Zijm 2016). Moreover, AM enables product delivery and repair times to be reduced by allowing the installation of AM printers close to (or even inside) customers' facilities (Pour et al. 2016). In light of this, spare parts SCs where items are produced via AM (in the following referred to as '*AM spare parts SCs*') have started to be considered a valid substitute for the traditional spare parts SC where items are produced with Conventional Manufacturing (CM) technologies (in the following referred to as '*CM spare parts SCs*') (Kilpi, Töyli, and Vepsäläinen 2009; Zijm, Knofius, and van der Heijden 2019). Hence, managers and practitioners need to understand when one is more economically profitable than the other (Baines et al. 2007; Davies 2004), considering also that AM spare parts SCs have some drawbacks with respect to the CM counterparts (e.g. higher costs of spare parts). As better described in Section 2, so far, this topic has been discussed only qualitatively (Holmström et al. 2010), and managers and practitioners are left alone in this decision. In fact, the available quantitative works dealing with AM spare parts focus either just on the production phase, trying to understand when it is convenient to switch from CM to AM technologies for producing items (Sgarbossa et al. 2021), or on the optimal configuration of the SCs considering only AM as the production technology (Khajavi, Partanen, and Holmström 2014) and not evaluating its benefits or drawbacks with respect to CM. As reported by Ghadge et al. (2018), the extant literature lacks methods to quantitative capture the differences between CM and AM SCs, also providing more robust evidence on when the adoption of AM SCs could ensure higher performance compared to a CM one. Therefore, a comparison between AM and CM spare parts SCs, trying to understand when one is more economically profitable than the other, is still missing. In this work, we aim to fill this gap, thus supporting managers and practitioners in deciding which spare parts SCs (AM or CM) to adopt. Since the decision of whether to embrace an AM spare parts SC or a CM one influences the spare parts SC configuration to adopt, this choice will be integrated into the DSS mentioned above. Therefore, the DSS developed herein will not only answer RQ1 (under which conditions is it economically profitable to have a centralised, decentralised, or hybrid spare parts SC configuration?) but also the following research question:

> **RQ2)** For the same case study, is it better to procure spare parts made with AM or CM?

Specifically, the proposed DSS is a decision tree developed by feeding and training a machine learning algorithm (decision tree algorithm) with the results of a parametric analysis where 10,000 different spare parts SC scenarios were considered (see Section 3 for more details). Specifically, we have limited the scenarios analysis to already existing SCs, where investments in new assets and facilities are not necessary, and only variable costs can be considered to optimally reconfigure the SC. Besides, we have investigated SCs of spare parts retailers, where only the storage and distribution of Stock-Keeping Units (SKUs) are owned by the company, while items production is entrusted to an external firm. This choice is made because, as stated by Zijm, Knofius, and van der Heijden (2019), most components in service companies are usually purchased from external suppliers and not produced internally. Finally, we have referred to the optimisation of two-echelon spare parts SC configurations, where spare parts replenishment comes from the external supplier to one or more DCs (first echelon). Then (second echelon), the DCs satisfy customer demand by delivering spare parts (Alvarez and van der Heijden 2014). This choice fits with Cohen, Zheng, and Agrawal (1997), in whose work a high number of echelons is reported to rarely occur in practice, rather indicating two-level SCs as more frequent. Anyway, no generality is lost by considering two-echelon SCs because they can easily be extended into multi-level ones if the depot of one layer is considered the base of the previous one (Ding and Kaminsky 2018).

The remainder of the present paper is as follows. In Section 2, a literature review is provided regarding models for configuring an SC (Section 2.1) and the impact of AM technologies on spare parts SCs (Section 2.2). In Section 3, the methodology followed to obtain the DSS is described. In Section 4, the DSS achieved is presented, and a discussion on the results is given, also showing its application to two case studies. Finally, in Section 5, some conclusions on this study are offered.

2. Literature review

In Section 2.1, existing methods for configuring an SC will be summarised. Due to the volatility and uncertainty of spare parts demand, we will focus on methods that are flexible against demand fluctuations, i.e. the so-called Dynamic Asset Deployment (DAD) methods (Cohen, Agrawal, and Agrawal 2006). Then, in Section 2.2, studies on AM deployment in spare parts SCs will be reviewed, showing advantages and disadvantages over CM.

2.1. Dad methods for SC configuration

DAD methods for configuring SCs are structured techniques to define what stocks to allocate throughout the geographical hierarchy of companies' DCs (Cohen, Agrawal, and Agrawal 2006), thus leading to centralised, decentralised, or hybrid SC configurations (Pyke and Cohen 1993). They differ from static methods in being flexible against demand fluctuations; hence they lead to a more effective SC configuration in the case of SKUs whose demand is difficult to forecast (Persson and Saccani 2007). As a result of applying DAD methods, the optimal distribution of each individual SKU is ensured, thus keeping near the customers the most critical articles while benefiting from risk pooling for the remaining ones (Stoll et al. 2015). Existing DAD methods for configuring SCs can be ranked into three categories: optimisation, simulation, and heuristic methods (Abdul-Jalbar et al. 2003; Muckstadt 2004). In DAD optimisation methods, an objective function is usually solved respecting some constraints by means of either exact or approximate analytical models, or algorithms (Roundy 1985). Initially, DAD optimisation methods were based on exact analytical models. An example of these is the METRIC method proposed by Sherbrooke (1968), which was also the first DAD optimisation method developed (Cavalieri et al. 2008; Muckstadt 2004). METRIC optimises stock levels of recoverable items in multi-item and multi-warehouse systems by minimising the sum of expected backorders. Several extensions and modifications of METRIC have been proposed over the years (e.g. (Muckstadt 1973; Muckstadt and Thomas 1980; Alfredsson and Verrijdt 1999)), as well as other DAD optimisation methods to configure SCs with null or non-null lead time (Federgruen and Zipkin 1984; Sherbrooke 1968), with or without backlogs (Alvarez and van der Heijden 2014), with an infinite or finite horizon of analysis (Zangwill 1966), with or without lateral transshipments (Patriarca et al. 2016), and nested or non-nested (Veinott 1969). An extended review of DAD optimisation methods is offered by Ding and Kaminsky (2019). Although accurate, DAD optimisation methods based on exact analytical models are difficult to solve since they are usually formulated as non-linear, integer, combinatorial, stochastic, non-stationary models (Cohen, Agrawal, and Agrawal 2006). Over the years, managers and practitioners have pointed out the need for more user-friendly and time-saving ways of configuring SCs (Cohen et al. 1990; Mintzberg 1989; Xie et al. 2008). For this reason, DAD optimisation methods based on approximate analytical models or algorithms were developed, allowing near-optimal solutions to be provided in a time-efficient way (Cohen, Kleindorfer, and Lee 1988; Daskin, Coullard, and Shen 2002; Graves 1985).

However, DAD optimisation methods based on algorithms or approximate analytical models were reported to not always lead to the optimal solution (Alvarez and van der Heijden 2014). To overcome this weakness, the second (simulation) and the third (heuristics) categories of DAD methods were developed. In DAD simulation methods, simulative models are developed, then carrying out ‘what if’ scenarios analyses (Xie et al. 2008). First, different SCs configurations are hypothesised (i.e. centralised, decentralised, or hybrid configurations). Then, the costs and benefits of each configuration are evaluated. Finally, the optimal case is selected among those considered based on simulation results. Some resolutions of DAD simulation methods are shown in Confessore, Giordani, and Stecca (2003) and Mofidi, Pazour, and Roy (2018). Xie et al. (2008) report that building a simulation model is often time-consuming and computationally challenging. Therefore, the use of simulation models should be reserved mainly to design complex SCs, such as those with many levels, where it is strictly necessary to reproduce and emulate all the control conditions and the variables impacting the real-life system (Lee, Padmanabhan, and Whang 1997). For the other SCs, instead, the last category of DAD methods (heuristic methods) can be used. Here, a near-optimal SC configuration solution (trade-off between costs, revenues, and service level) is achieved (Schwarz 1973) by using spare parts classification (Persson and Saccani 2007; Roda et al. 2014) or big data analytics (Cohen and Lee 1990). DAD heuristic methods based on spare parts classification use a range of criticality criteria to rank and group items (Teunter, Babai, and Syntetos 2010). Then, group membership is exploited to guide rules for asset deployment and inventory replenishment, as shown by Lee et al. (2014) and Stoll et al. (2015). Conversely, DAD heuristic methods based on big data analytics typically use machine learning techniques to predict the performance of different SC configurations and identify the most profitable solution, as shown by Xie et al. (2008).

According to Gregersen and Hansen (2018), whatever category of DAD methods is chosen, DAD methods for configuring SCs are usually composed of two steps. First (Step 1), the asset deployment policy is defined, determining for each SKU whether to opt for a centralised, decentralised, or hybrid SC configuration (Cantini et al. 2021). Then (Step 2), the inventory control policy is decided, planning which spare part to supply and which to order on-demand, and also establishing how many items to replenish and how often (Caron and Marchet 1996). The existing literature on SC configuration is mainly focused on optimising Step 2, determining optimal (or near-optimal) reordering policies for each SKU by minimising operational costs (Abdul-Jalbar et al. 2003; Cohen, Zheng, and Wang 1999; Roundy 1985). On the contrary, fewer investigations were carried out concerning Step 1, especially when dealing with spare parts SCs. Indeed, Milewski (2020) reports that, although it has been known for a long time that efficient spare parts logistics strongly affects the SC’s economy, the choice between centralised, decentralised or hybrid SC configurations is still overlooked in the literature. Farahani et al. (2015) state that the first paper to deal with this topic was by Eppen (1979). However, this study focuses only on centralised and decentralised SC configurations, neglecting hybrid SC configurations. Moreover, it cannot be applied in the case of spare parts SCs since it addresses products whose demand has a normal distribution, while spare parts demand follows a Poisson distribution. Other recent efforts to compare spare parts SC configurations (Holmström et al. 2010; Liu et al. 2014) are also affected by some shortcomings. In fact, Holmström et al. (2010) give a qualitative discussion, while, according to Khajavi, Partanen, and Holmström (2014), the analysis should be quantitative and based on the minimisation of SC costs. On the other hand, the study by Liu et al. (2014) considers only centralised and decentralised SC configurations, neglecting hybrid configurations. Moreover, the comparison among the two configurations is carried out only in terms of theinventory level, neglecting, for example, inventory and transportation costs.

As confirmed by Tapia-Ubeda et al. (2020), the topic of choosing between centralised, decentralised, and hybrid SC configurations is not the subject of much scientific research, and there is potential for further studies. This literature gap is the starting point of the present study, in which a heuristic DSS is proposed to assist in the process of configuring spare parts SCs. The presented DSS compares different SC configurations, choosing the optimal solution between centralisation, decentralisation, or hybrid configurations, and including in the analysis the costs of purchasing spare parts, inventory costs, the costs of sending out replenishment orders, transportation costs, and backorder costs.

2.2. AM deployment in spare parts SCs

The deployment of AM technologies for manufacturing spare parts has recently attracted great interest, getting the spotlight in scientific research (Li et al. 2019). In fact, according to several authors (Holmström et al. 2010; Pérès and Noyes 2006; Silva and Rezende 2013; Zijm, Knofius, and van der Heijden 2019), AM has the potential to revolutionise spare parts SCs thanks to two main benefits over CM technologies. The first is that spare parts manufacturing is allowed to be on-demand (Berman 2012). Hence, there is no need for downstream stocks across the SC, and the holding costs incurred are low, thus enabling AM spare parts SCs to be more cost-effective than CM ones (especially decentralised CM SCs, where there would be several DCs, each with high inventory levels). The second benefit is that transportation lead times can be reduced since production is enabled to be near consumers (moving AM printers near or inside customers' facilities). As a result, shorter lead times could be ensured, thus obtaining a decentralised SC where design and production are closely intertwined. This characteristic reduces the time-to-market, transportation costs, and downtime costs for broken machines, providing benefits over CM, especially for configuring SCs in geographically or temporally isolated systems (Westerweel et al. 2021).

However, according to Pour et al. (2016) and Zijm, Knofius, and van der Heijden (2019), AM spare parts SCs are characterised by two main disadvantages compared to CM counterparts. The former is that high initial investment costs need to be paid to buy AM printers (although these are decreasing due to the development of AM technology). This aspect could make AM spare parts SCs less cost-effective than the CM ones, especially in the case of decentralised SC configurations, since at least one AM printer should be installed in each DC. The second disadvantage is that production costs are often higher than the CM ones, and the production time is longer. Indeed, the speed of AM technologies is slower compared to CM, while longer post-processing and inspection times are required to ensure the reliability and quality of the spare parts. Consequently, SC costs and lead times could be higher, especially in centralised SC configurations where the central DC is not very close to customers' facilities.

Besides, when considering the labour cost in the economic analysis to decide the most cost-effective manufacturing technology, it is not yet clear whether AM would lead to benefits over CM or not. On the one hand, when deploying AM technologies, one operator can control more AM printers. Therefore, fewer operators are needed, and a reduction of the manual labour cost as a percentage of the overall product price is ensured. On the other hand, highly trained operators are required to use digital AM technologies, thus increasing the average labour cost per hour.

Up to now, when evaluating the possibility of adopting AM spare parts SCs, many studies have focused only on the production phase, investigating the convenience of manufacturing AM rather than CM items (Costabile et al. 2017; Knofius, van der Heijden, and Zijm 2016; Sgarbossa et al. 2021) and which AM technologies to use (Khajavi et al. 2018; Zhang, Zhang, and Han 2017). Other activities, such as logistics, have so far been neglected, while the impacts of AM in all areas of spare parts SCs should be considered before deciding whether to adopt it or not. This becomes even more important if we include in the analysis different SC configurations (centralised, decentralised, and hybrid), since the choice of a specific spare parts SC configuration might be affected by the costs and characteristics of the manufacturing technology considered (Li et al. 2019). To date, however, only two works have tried to integrate the choice of the manufacturing technology with the selection of the spare parts SC configuration (Li et al. 2017; Liu et al. 2014). These works only consider centralised or decentralised configurations without focusing on hybrid spare parts SC configurations. Moreover, they select the optimal spare parts SC design (from now on, we will refer to 'spare parts SC design' as the activity to decide the optimal spare parts SC configuration together with the choice of the manufacturing technology) based on the results of simulation models. Therefore, their considerations refer to a specific case study and cannot be generalised. To the best of our knowledge, there is no structured method to support managers and practitioners in the process of designing spare parts SCs. This problem is overcome in this paper, where a DSS is developed to solve the literature gap identified in Section 2.1 (assisting managers and practitioners in the process of configuring spare parts supply chains), also including the choice of the optimal manufacturing technique (AM or CM).

3. Methodological framework

The main objective of this paper is to develop a DSS to assist managers and practitioners in designing spare parts SCs (which means deciding both the spare parts SC configuration and the manufacturing technology). The proposed DSS is a decision tree that is derived from a cost-based comparison of over 10,000 different spare parts SCs scenarios (i.e. spare parts SCs characterised by different spare parts demand, purchasing costs, transportation costs, backorder costs, and required service level) of ten different supply chain designs. To this end, four main steps were performed. However, before describing these steps, it is useful to clarify some key characteristics of the DSS and some assumptions made.

Dealing with the key characteristics, the DSS is developed for managers and practitioners interested in two-echelon SCs, where spare parts are bought from an external supplier (not produced internally), stored in one or more DCs, and distributed to fulfil the product demand at multiple customer locations. Hence, the control volume underlying this study is shown in Figure 1, where the final customer may also be a subsequent retailer, as reported by Fathi et al. (2021).

The proposed DSS supports managers and practitioners in choosing between ten spare parts SC designs, derived by combining two manufacturing technologies (AM and CM) with five spare parts SC configurations (ranging from centralisation to decentralisation passing through three hybrid configurations). A schematic representation of the five SC configurations considered is

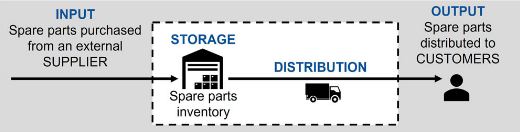

Figure 1. Control volume considered to develop this study (within the dashed rectangle).

depicted in Figure 2, considering the example of a company purchasing spare parts from a supplier and serving six customers. The different spare parts SC configurations are identified through a parameter called 'degree of centralisation' (*Deg*). Such parameter, based on the paper by Gregersen and Hansen (2018), is equal to one in the case of full centralisation, while it is the ratio between the number of DCs (*#DC*) able to answer customers' demand and the number of customers to be served (*#customers*) in hybrid and decentralised SC configurations (Equation (1)).

$$Deg = degree\ of\ centralisation$$
$$= \begin{cases} 1\ full\ centralised\ SC\ configuration \\ 1 - \frac{\#DC}{\#customers} else \end{cases} \quad (1)$$

As can be seen from Figure 2, the five different spare parts SC configurations considered in this work are those with *Deg* equal to 0 (decentralised configuration), 0.25 (hybrid configuration), 0.50 (hybrid configuration), 0.75 (hybrid configuration), and 1 (centralised configuration), and this choice was made to cover the range of possible SC configurations well. As an example, Figure 2 provides a schematic representation of the SC configurations considered in the case of a two-echelon SC serving six customers. In Figure 2, different locations are analysed for spare parts DCs. Instead, the supplier of the DCs is not shown, being represented by dashed arrows to indicate that it is out of control volume, and that we are not interested in its geographical location, but only in its average lead time.

Figure 3, then, summarises the ten different spare parts SC designs considered by the DSS.

Concerning the assumptions made in the development of the DSS, these are listed below.

(1) A single external supplier is assumed based on the work by Farahani et al. (2015), who, based on the fact that several suppliers offer similar products, indicated that it is more efficient to consider a single supplier to serve subsequent DCs;
(2) Spare parts are assumed to be purchased from an external supplier (not produced in-house); this means that the costs of purchasing spare parts include all the costs that the supplier incurs. These costs include the costs of producing spare parts (also considering quality control activities), the fixed costs of AM/CM equipment, the costs of digitalising AM items, thus converting 2D drawings into 3D designs, and the profit margins that suppliers want to achieve (Pour et al. 2016);
(3) Based on Tapia-Ubeda et al. (2020), no capacity constraints are considered for the supplier's warehouse and the DCs. Hence, it is assumed that each facility is able to keep inventories without space limitations;
(4) Lead times are deterministic, as suggested by Schwarz (1973) and Cohen, Kleindorfer, and Lee (1988), while spare parts demand is stochastic, following a Poisson distribution as suggested, e.g. by Stoll et al. (2015) and Sherbrooke (1968);
(5) Decentralised DCs are considered to be geographically equidistant from the customer: in such a way that the DCs are characterised by the same lead times and transportation costs. Moreover, the transportation costs in decentralised SC designs are considered negligible since each decentralised DC is supposed to be positioned close to the specific customer that it serves;
(6) No reverse logistics (possibility of repairing and reusing broken spare parts) is considered, as suggested by Zijm, Knofius, and van der Heijden (2019), since the focus of this study is not the problem of sustainability in the SCs, but rather the SC design;
(7) No lateral transhipments are admitted, as shown by Schwarz (1973);

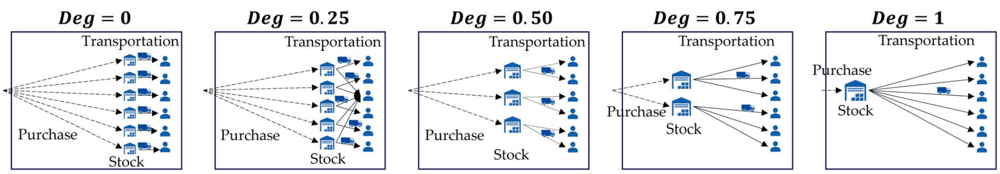

Figure 2. Schematic representation of the five SC configurations considered. ***Deg*** equal to 0 corresponds to a decentralised SC configuration, ***Deg*** equal to 1 is a centralised configuration, and the values in between are hybrid SC configurations. The picture considers an example of a two-echelon SC serving six customers.

	Deg = 0	Deg = 0.25	Deg = 0.50	Deg = 0.75	Deg = 1
AM	1 AM, Deg = 0 (full decentralization)	3 AM, Deg = 0.25 (hybrid config.)	5 AM, Deg = 0.50 (hybrid config.)	7 AM, Deg = 0.75 (hybrid config.)	9 AM, Deg = 1 (full centralization)
CM	2 CM, Deg = 0 (full decentralization)	4 CM, Deg = 0.25 (hybrid config.)	6 CM, Deg = 0.50 (hybrid config.)	8 CM, Deg = 0.75 (hybrid config.)	10 CM, Deg = 1 (full centralization)

Figure 3. Matrix of the spare parts SC designs considered in the DSS.

(8) Since the focus of this study is not the problem of sustainability in the SCs, but rather the SC design, no environmental effects of different SC designs are assessed. For example, CO2 emitted during transportations is neglected;
(9) Only variable costs are considered (see Section 1), not assessing initial investment costs in facilities, or assets;
(10) Spare parts transportation costs are calculated by assuming that only one spare part is distributed per trip. This hypothesis is considered acceptable because spare parts demand follows a Poisson distribution, also known as the law of rare events.

In addition, to develop the DSS, some modelling and spare parts management choices were taken, which are listed in the following remarks.

(1) Warehouses are managed according to a continuous inventory control policy. Given the nature of lead times and demand, the selected inventory policy is (s,Q), where *s* is the reorder level and Q is the economic order quantity. Indeed, Fathi et al. (2021), Ivanov (2021), and Sapna Isotupa (2006) suggest such an inventory control policy as the optimal one in the case of stochastic demand and deterministic lead time;
(2) The average annual demand of one customer is known, as well as the number of customers to be served, as shown by Cohen, Kleindorfer, and Lee (1988);
(3) The duration of the period considered to develop the analysis is one year, as done by Daskin, Coullard, and Shen (2002). It is worth mentioning that this information is not a simplifying assumption, but it is here listed to underline that the total costs of SCs are calculated over a time horizon of one year, as well as the values of (s, Q) needed to control the inventory replenishment of DCs. The mathematical model and the analysis provided below could also be repeated by considering smaller or larger time horizons;
(4) The risk of obsolescence is considered included within the holding cost rate. This choice is in line with what reported by Khajavi, Partanen, and Holmström (2014), who showed that the inventory obsolescence cost in a DC can be calculated as a function of the inventory level and of an annual part obsolescence rate. Therefore, in the present study, the annual part obsolescence rate is considered contained within the holding cost rate;
(5) SKUs are supposed to be producible with both AM and CM. This assumption is introduced to allow the comparison between SCs where the distributed spare parts are of AM or CM type, thus answering the second research question (RQ2). However, in the case that some parts are not producible with AM technologies (as shown by Zijm, Knofius, and van der Heijden (2019)), it is possible to use the mathematical model here proposed only by comparing SC designs with CM items (numbers 2, 4, 6, 8, and 10 in Figure 3). Viable method for selecting spare parts suitable for AM are offered by Chaudhuri et al. (2021) and (Frandsen et al. 2020);
(6) A single-item approach is adopted, choosing for each individual SKU the optimal SC design. This derives from the works by Stoll et al. (2015) and Cohen, Agrawal, and Agrawal (2006), who suggested that an effective SC configuration should adopt a single-item approach to ensure the optimal distribution of each individual SKU.

Now that the key characteristics of the proposed DSS and the assumptions made have been described, the four main steps followed to develop the DSS can be discussed. In Step 1, a mathematical model to compare the cost-effectiveness of the ten spare parts SC designs was developed. Then, in Step 2, an analysis of variance (ANOVA) was performed to determine the most relevant input parameters of the mathematical model, thus checking if any of them have a negligible impact on the selection of the optimal SC design. In Step 3, a parametric analysis was performed to investigate a sample of 10,000 realistic spare parts SC scenarios (i.e. spare parts SCs characterised by different spare parts demand, purchasing costs, transportation costs, backorder costs, and required service level) collected by varying the most relevant input parameters of the mathematical model (emerging from Step 2). Finally, in Step 4, the DSS was obtained in the

Table 1. Input parameters for the mathematical model.

Input parameter	Description	Unit measure
i	Considered SC design. i can assume integer values between 1 and 10 according to Figure 3	[–]
j	Manufacturing technology of the purchased spare parts. j can be AM or CM	[–]
$\#customers$	Number of customers served by the company	[–]
$ELTSL$	Desired expected lead time service level$ELTSL$	[–]
$\bar{D}_{1customer}$	Average annual demand for SKU emitted by one customer	[units/time]
Deg_i	Degree of centralisation in SC configuration i. It assumes a specific value according to Figure 3[a]	[–]
$etcentral_i$	Unitary external transportation cost from the central DC to customers. It only refers to centralised SC configurations ($i = 9$ or$i = 10$)	[€/transportation]
$uback$	Unitary cost of one backorder of SKU	[€/backorder]
L_j	Lead time needed by the supplier to deliver the j-th SKU to DCs	[time]
uc_j	Unitary cost of purchasing the j-th SKU from the supplier	[€/unit]
mh	Hourly labour cost	[€/time]
ot	Average time needed to send one replenishment order	[time]
$h_{\%}$	Holding cost rate for keeping inventory of SKU	[€/time$*$unit]

[a] Deg_i is 0 if i is equal to 1 or 2, is 0.25 if i is equal to 3 or 4, is 0.5 if i is equal to 5 or 6, is 0.75 if i is equal to 7 or 8, while is 1 if i is equal to 9 or 10.

form of a decision tree by leveraging a machine learning algorithm (specifically a decision tree algorithm) fed with the results of the parametric analysis. Each step is described in detail below in a specific section.

3.1. Mathematical model

In Step 1 of the development of the DSS, a mathematical model was established to compare the costs of the considered spare parts SC designs, thus allowing the optimal design to be identified. Table 1 lists the model input parameters.

According to the assumption, the costs are related to a single item, and therefore the optimal spare parts SC design is the one that minimises the spare parts SC total costs ($Ctot_i$) for a single SKU (Equation (2)).

$$\min[Ctot_i] \; with \; i = 1,\ 2,\ \ldots,\ 10 \tag{2}$$

where $Ctot_i$ is calculated according to Equation (3) as the sum of the costs of purchasing spare parts ($PC_{i,j}$), placing supply orders ($OC_{i,j}$), holding inventory ($HC_{i,j}$), transporting spare parts from DCs to customers (ETC_i), and backorders (BC_i).

$$Ctot_i = PC_{i,j} + OC_{i,j} + HC_{i,j} + ETC_i + BC_i \tag{3}$$

Specifically:

$PC_{i,j}$ (the total cost of purchasing spare parts from the external supplier for a specific SC design i), according to Equation (4), is given by the product between the unitary cost of the spare part (uc_j), the number of DCs in the SC ($\#DC_i$, Equation (5)), and the average annual demand in each DC ($\overline{Dtot_i}$, Equation (6)).

$$PC_{i,j} = uc_j * \overline{Dtot_i} * \#DC_i \tag{4}$$

$$\#DC_i = \begin{cases} [(1 - Deg_i) * \#customers]^+ \; if \; i = 1, 2, \ldots, 8 \\ 1 \; if \; i = 9, 10 \end{cases} \tag{5}$$

$$\overline{Dtot_i} = \begin{cases} \left(\frac{\bar{D}_{1\,customer} * \#customers}{\#DC_i}\right) if \; i = 1, 2, \ldots, 8 \\ (\#customers * \bar{D}_{1\,customer}) if \; i = 9, 10 \end{cases} \tag{6}$$

$OC_{i,j}$ (the total cost of placing orders for replenishing DCs' inventories), according to Equation (7), is given by the product between the unitary cost of placing one order (oc, Equation (8)), the average number of orders ($\#orders_{i,j}$, Equation (9)), and the number of DCs ($\#DC_i$).

$$OC_{i,j} = (oc * \#orders_{i,j}) * \#DC_i \tag{7}$$

$$oc = mh * ot \tag{8}$$

$$\#orders_{i,j} = \frac{\overline{Dtot_i}}{Q_{i,j}} \tag{9}$$

where $Q_{i,j}$ is the economic order quantity for replenishing SKUs in DCs calculated using Wilson's formula (Stoll et al. 2015) (Equation (10)), and h_j is the unitary holding cost in each DC (Equation (11)).

$$Q_{i,j} = \sqrt{\frac{2 * \overline{Dtot_i} * oc}{h_j}} \tag{10}$$

$$h_j = uc_j * h_{\%} \tag{11}$$

$HC_{i,j}$ (the total holding cost), according to Equation (12), is given by the product between the unitary holding cost, the average inventory in each DC ($I_{i,j}$, Equation (13)), and the number of DCs ($\#DC_i$).

$$HC_{i,j} = (h_j * I_{i,j}) * \#DC_i \tag{12}$$

$$I_{i,j} = \frac{Q_{i,j}}{2} + SS_{i,j} \tag{13}$$

Where $SS_{i,j}$ are the safety stocks in each DC, corresponding to the smallest value that satisfies Equation (14), thus compensating demand fluctuations (Equation (15)) and avoiding stock-outs at least to ensure the desired service level.

$$1 - \sum_{n=0}^{SS_{i,j}-1} \left[\frac{(\overline{Dtot\ in\ lead\ time_{i,j}})^n}{n!} * e^{-\overline{Dtot\ in\ lead\ time_{i,j}}} \right] \geq (1 - ELT\ SL) \quad (14)$$

$$\overline{Dtot\ in\ lead\ time_{i,j}} = \overline{Dtot_i} * L_j \quad (15)$$

ETC_i (the total transportation cost to deliver spare parts from DCs to customers), according to Equation (16), is given by the product between the unitary external transportation costs (et_i, Equation (17)), the average demand ($\overline{Dtot_i}$), and the number of DCs ($\#DC_i$).

$$ETC_i = (et_i * \overline{Dtot_i}) * \#DC_i \quad (16)$$

$$et_i = \begin{cases} et\ decentral_i\ if\ i = 1, 2, \ldots, 8 \\ et\ central_i\ if\ i = 9, 10 \end{cases} \quad (17)$$

where the unitary external transportation costs for decentralised and hybrid configurations ($etdecentral_i$) is defined according to Equation (18) (for more information on Equation (18) see Appendix A).

$$et\ decentral_i = et\ central_i * f(Deg_i) \quad (18)$$

Finally, BC_i (the total cost of backorders), according to Equation (19), is given by the product between the unitary backorder cost ($uback$), the average number of backorders ($\#backorders_i$,Equation (20)), and the number of DCs ($\#DC_i$).

$$BC_i = (uback * \#backorders_i) * \#DC_i \quad (19)$$

$$\#backorders_i = [(1 - ELT\ SL) * \overline{Dtot_i}]^+ \quad (20)$$

3.2. ANOVA analysis

In Step 2 of the development of the DSS, an analysis of variance (ANOVA) was used to define if all the input parameters (Table 1) strongly impact the selection of the optimal SC design or if any of them have a negligible effect. To this end, a preliminary parametric analysis was first carried out. In the preliminary parametric analysis, the parameters $mhmh$, ot, and $h_{\%}$ in Table 1 were assumed fixed and equal to 30 €/h, 10 min, and 25% respectively, while the remaining independent variables of Table 1 (excluding i, which already had predefined values, and differentiating cost items in the case of AM or CM manufacturing) were associated with a range of realistic discrete admissible values (Table 2). As shown in Table 2, three values were considered for each parameter, where two of them (the extremes) were defined by consulting the sources in the last column of Table 2, while the third value was taken as the intermediate number. This resulted in a total of 729 different combinations of the input parameters (each combination of input parameters is what we refer to as '*scenario*'), which were then used in the mathematical model of Step 1 to determine the optimal spare parts SC design for each scenario. Finally, the results were subjected to an ANOVA using Minitab software, where the parameters listed in the first column of Table 2 were indicated as input factors, while the optimal SC design outcomes were indicated as responses. It is worth mentioning that the ANOVA was performed allowing variables to assume only three discrete values to obtain easily understandable graphs in which the trend of the curves could be immediately recognised, thus revealing the impact of the parameters on the decision.

3.3. Parametric analysis

After performing the ANOVA, parameters whose impact is negligible concerning the suggestion of the optimal SC design were excluded from the study. Conversely, the input parameters with a significant influence on the results were considered in Step 3 of the development of the DSS.

Aiming to obtain a DSS in the form of a decision tree, a dataset was required to feed and train the decision tree algorithm. For this reason, in Step 3, another parametric analysis was developed to collect and investigate a sample of 10,000 realistic spare parts SC scenarios (with different demands, costs, and service levels). Overall, the process of obtaining the data used to conduct this parametric analysis can be summarised as follows. First, the parameters mh, ot and $h_{\%}$ in Table 1 were again assumed fixed (considering the same values mentioned in Section 3.2), while the independent non-negligible parameters resulting from Step 2 were associated with a range of realistic admissible values defined within upper and lower limits. As upper and lower limits, the same extreme values of the ranges in Table 2 were chosen. However, unlike the parametric analysis of Step 2, here the parameters were not allowed to take on only three values, but rather intermediate values were assigned using the Sobol quasi-random low discrepancy sequence (Burhenne, Jacob, and Henze 2011). Hence, each parameter (par) was represented as a set of values uniformly distributed over a range determined according to Equation (21).

$$par = par_{lower\ limit} + Sobol \cdot (par_{upper\ limit} - par_{lower\ limit}) \quad (21)$$

Table 3 reports the range of admissible values for the Sobol-based parametric analysis.

Then, by randomly mixing the values of the input parameters, a sample of 10,000 scenarios was collected, where, for each scenario, the mathematical model of Step

Table 2. Parameters and values of discretised parametric analysis.

Input parameter	Admissible values	Unit measure	Source used to define the admissible values
#customers	5; 53; 100	[–]	Authors' experience[a]
ELTSL	0.85; 0.92; 0.99	[–]	Authors' experience
$\bar{D}_{1customer}$	1; 4; 7	[units/year]	(Knofius et al. 2021)
$etcentral_i$	100; 1,050; 2,000	[€/transportation]	Authors' experience
uback	1,000; 50,500; 100,000	[€/backorder]	(Peron et al. 2021)
L_{AM}	1; 2.5; 4	[weeks]	(Knofius et al. 2021)
L_{CM}	4; 15; 26	[weeks]	(Knofius et al. 2021)
uc_{AM}	100; 1,300; 2'500	[€/unit]	(Knofius et al. 2021)[b]
uc_{CM}	10; 1,255; 2,500	[€/unit]	(Knofius et al. 2021)[c]

[a]The over twenty years' experience of some of the authors in the field of logistics and spare parts management combined with the consultation of expert staff from spare parts distribution companies make these assumptions reliable.
[b]Knofius et al. (2021) considered 1197 €/unit. We have assumed a wider range.
[c]Knofius et al. (2021) reported that the cost of CM parts is typically lower than AM ones, but this does not always hold true (it depends on the part complexity). Hence, we assumed a minimum value lower than AM, but the same upper limit.

Table 3. Values considered in the Sobol-based parametric analysis. The range extreme values are based on Table 2.

Input parameter	Range of admissible values	Unit measure
#customers	integers between 5 and 100	[–]
ELTSL	floats between 0.85 and 0.99	[–]
$\bar{D}_{1customer}$	integers between 1 and 7	[units/year]
$etcentral_i$	floats between 100 and 2,000	[€/transportation]
uback	floats between 1,000 and 100,000	[€/backorder]
L_{AM}	integers between 1 and 4	[weeks]
L_{CM}	integers between 4 and 26	[weeks]
uc_{AM}	floats between 100 and 2,500	[€/unit]
uc_{CM}	floats between 10 and 2,500	[€/unit]

1 (Section 3.1) was applied, determining the optimal SC design.

It should be noted that the Sobol quasi-random low discrepancy sequence was chosen based on the study by Burhenne, Jacob, and Henze (2011), who report that, when studying problems with a large number of input variables, the Sobol sequence is expected to be more effective in exploring the input variable space in comparison to other sampling strategies (i.e. discrete sampling, Monte Carlo, or Latin Hypercube).

3.4. Decision tree

Finally, in Step 4, the DSS in the form of a decision tree was generated, constituting a guideline for managers and practitioners to understand which spare parts SC design is the optimal (more cost-effective) for them. To develop such DSS, a decision tree algorithm was used. A decision tree algorithm is a supervised classification technique, and it predicts the class to which an item belongs based on a given set of attributes (Nugroho, Adji, and Fauziati 2015). Here, the results of the parametric analysis (Step 3) were used as the dataset for training the decision tree algorithm (using Python's Sklearn library), where for each scenario:

- The values of the non-negligible input parameters were given as input attributes.
- The optimal spare parts SC design determined by applying the mathematical model was indicated as the final class label that the decision tree algorithm should learn to predict.

Therefore, the decision tree was obtained as follows. Starting at a root node, the dataset was recursively split into binary subsets (branches) based on the Gini diversity index (*gdi*, Equation (22)), where K is the number of class labels (the ten spare parts SC designs defined in Figure 3), and $p(k)$ is the probability of picking the data point with the class$k$ (Shaheen, Zafar, and Ali Khan 2020). *gdi* measures the probability of a given data point from the dataset being wrongly classified when it is randomly chosen (Arena et al. 2022). Hence, $gdi = 0$ means that all data points of the dataset belong to a certain class, while $gdi = 1$ implies that the data points are randomly distributed across different classes.

$$gdi = 1 - \sum_{k=1}^{K} p(k)^2 \qquad (22)$$

At each node of the tree, an attribute and its cut point were chosen to generate two branches with the aim of minimising Equation (23), thus identifying the split which provided the maximum purity.

$$\min\left(\frac{n_{left}}{n} gdi_{left} + \frac{n_{right}}{n} gdi_{right}\right) \qquad (23)$$

In Equation (23), n is the number of data points in the original node, n_{left} is the number of data points in the new node on the left branch, n_{right} is the number of data points in the new node on the right branch, gdi_{left} is the Gini diversity index in the new node on the left branch, and, finally, gdi_{right} is the Gini diversity index in the new node on the right branch (Sgarbossa et al. 2021). The elements at the end of the tree, obtained after the last branch split, are called leaves, and the number of splits performed coincides with the number of levels (depth) of the tree.

Seeking to generate a user-friendly DSS, the decision tree was pruned by imposing a maximum depth ($Dmax$, maximum number of splits of the starting dataset into sub-branches before reaching a leaf). This pruning activity was also useful to avoid the over-fitting problem when generating the tree (Morgan et al. 2003). For the pruning purpose, a sensitivity analysis of the total accuracy (A) of the decision tree was performed by imposing different values for $Dmax$, and determining the resulting A calculated as the ratio between the number of correct predictions ($\#correctpredictions_{tree}$) and the number of total predictions ($\#predictions_{tree}$, initial dataset size) (Equation (24)).

$$\boldsymbol{A} = \frac{\#correct\ predictions_{tree}}{\#predictions_{tree}} \tag{24}$$

The decision tree representing a trade-off between the accuracy of predictions and user-friendliness was then proposed as a DSS. Finally, the effectiveness of the selected decision tree was evaluated based on three key performance indicators (KPIs) related to the leaves of the tree. The first KPI is the accuracy of each leaf (a, Equation (25)), given by the ratio between the number of correct predictions ($\#correctpredictions_{leaf}$) and the number of total predictions in the leaf ($\#predictions_{leaf}$). The second KPI is the number of elements reaching each leaf (p, Equation (26)), given by the ratio between the number of elements classified within that leaf ($\#predictions_{leaf}$) and the number of total elements to be classified ($\#predictions_{leaf}$). The last KPI is the average percentage increase in cost that occurs when the wrong option is selected in the leaf (c, Equation (27)), obtained as the arithmetic mean of the cost increase generated by each wrong prediction.

$$a = \frac{\#correct\ predictions_{leaf}}{\#predictions_{leaf}} \tag{25}$$

$$p = \frac{\#predictions_{leaf}}{\#predictions_{tree}} \tag{26}$$

$$c = \frac{\sum_{k=1}^{\#wrong\ predicions_{leaf}} \left(\left| \frac{\mathrm{cost} of\ wrong\ prediction\ - cost\ of\ correct\ prediction_k}{cost\ of\ correct\ prediction_k} \right| *100 \right)}{\#uncorrect\ predictions_{leaf}} \tag{27}$$

4. Results and discussion

As mentioned in Section 3, having developed the mathematical model to compare the costs of different SC designs (Step 1, Section 3.1), the next step conducted was the development of an ANOVA (Step 2, Section 3.2), whose results are shown in Figure 4.

Figure 4 proves that three out of the nine input parameters considered (Table 2) have a negligible impact on the process of selecting the optimal spare parts SC design. In fact, when varying the three discrete values assumed by L_{AM}, L_{CM}, and $ELTSL$, the curve obtained in the Main Effects Plots relative to the mean of the optimal SC designs is almost horizontal. Therefore, the effect of the parameters L_{AM}, L_{CM}, and $ELTSL$ on the selected spare parts SC design can be considered null. On the contrary, the remaining parameters show a non-negligible impact on this decision-making process.

Given the ANOVA results, the L_{AM}, L_{CM}, and $ELTSL$ parameters were not considered for building the DSS, being excluded from the implementation of the parametric analysis (Step 3 in Section 3.3). Instead, the remaining six parameters were associated with Sobol values as indicated in Table 3. Then, such values were randomly joined together to create a sample of 10,000 realistic spare parts SC scenarios, and for each scenario the optimal spare parts SC design was determined through the mathematical model of Section 3.1. As described in Section 3.4, the results were then used to feed a decision tree algorithm, where the values assumed by the input variables in the different scenarios were used as input attributes, while the identifier of the optimal spare parts SC designs was indicated as the final class label.

Aiming to obtain a DSS that is both easy-to-use (that corresponds to an easy-to-read decision tree) and accurate, we carried out a sensitivity analysis of the total accuracy A of the decision to determine how to prune the branches (Figure 5). Based on the results depicted in Figure 5, we decided to use as DSS the decision tree with $Dmax = 4$ (red circle in Figure 5) since it represents a trade-off between user-friendliness and accuracy. Figure 6 shows the decision tree with $Dmax = 4$.

It is interesting noting that not all the six non-negligible parameters identified from the ANOVA analysis are used in the decision tree ($\bar{D}_{1customer}$ is missing), suggesting that some parameters are more important on the optimal SC design choice than others. This is confirmed by Figure 7, that shows the relative importance of the independent parameters on the choice of the optimal SC design (the relative importance is calculated first combining the changes in the Gini Diversity Index weighted by the node probability due to splits at each parameter, then dividing the sum by the number of branch nodes

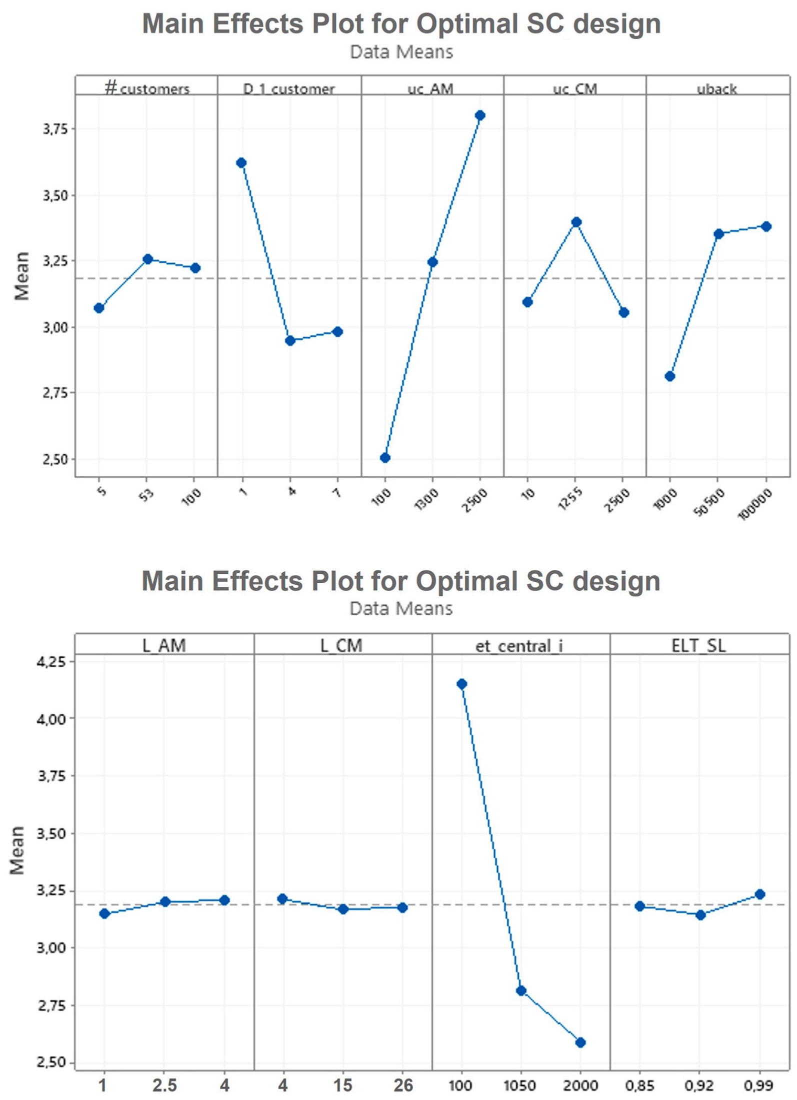

Figure 4. Results of the ANOVA (Main Effects Plots) for the optimal SC design.

(Lolli et al. 2022)). From the relative importance, in fact, it emerges that uc_{CM} and uc_{AM} are the two parameters that influence the most the choice of the optimal SC design (the first decision on the decision tree is in fact made on uc_{CM}), followed by *uback* and $etcentral_i$. The relative importance of $\bar{D}_{1customer}$ is instead low, meaning that this parameter has a weaker impact on the SC design decision, and for this reason, when pruning the tree, $\bar{D}_{1customer}$ does not appear in Figure 6.

Moreover, the decision tree in Figure 6, shows that the most recommended spare parts SC designs in the DSS are those with AM/CM and $Deg_i = 0.25$ (spare parts SC designs 3–4), which are suggested in eleven out of sixteen leaves of the tree. Given the frequent cost-effectiveness of such spare parts SC designs, this study demonstrates the importance of considering hybrid spare parts SC configurations in the analysis, not only comparing centralised and decentralised spare parts SC configurations. In particular, spare parts SC design 3 with AM and $Deg_i = 0.25$ is more cost-effective than the others whenever uc_{CM} is higher than 1,490 €/unit and the cost of one backorder (*uback*) is higher than 38,175 €/backorder. In fact,

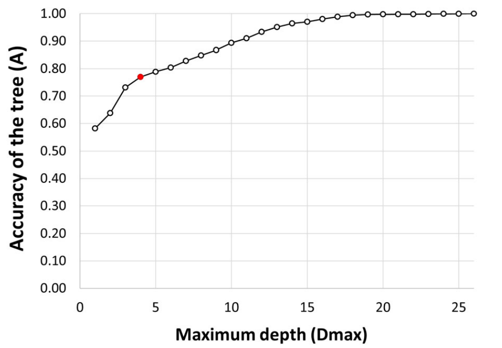

Figure 5. Sensitivity analysis on the accuracy (A) of the decision tree.

in such a case, the unitary cost of purchasing AM spare parts is similar to or lower than the CM one, so an AM spare part SC design is usually preferable. In addition, in such a case, a hybrid spare parts SC configuration with a low degree of decentralisation (0.25%) reduces backorders by benefiting from the risk-pooling effect (the demand is aggregated in a few DCs) while keeping delivery times and costs lower than in fully centralised SC configurations.

Conversely, the leaves of the decision tree in Figure 6 do not include spare parts SC designs 5–9, indicating that, generally, SCs with Deg_i of 0.50 and 0.75 are not cost-effective, as well as the total centralisation of AM spare parts. Moreover, Figure 6 shows the KPIs (a, p, and c, Section 3.4) of the decision tree with $Dmax = 4$, demonstrating that some leaves have very high accuracy ($a >$ 90%), which guarantees the reliability of the predictions, while others have low accuracy ($a <$ 50%), which seems insufficient to trust the DSS. However, the increase of cost (c) that managers and practitioners should pay in the case of a wrong decision is always less than 10% (often even below 5%) and this means that an incorrect prediction of

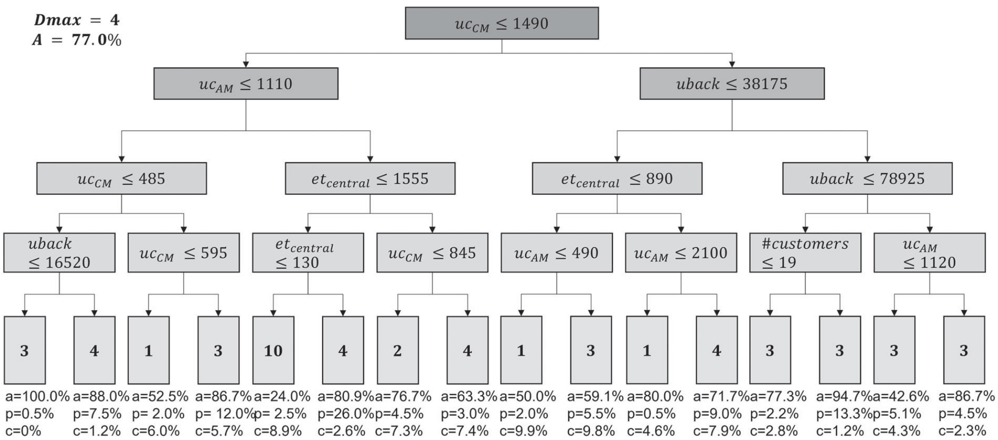

Figure 6. Decision tree with a maximum depth of 4 levels ($Dmax = 4$).

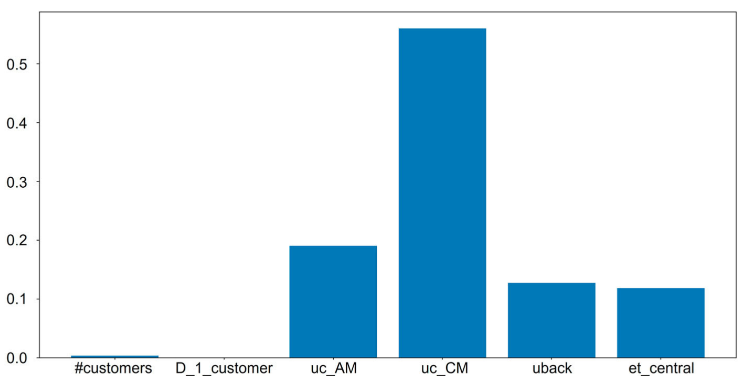

Figure 7. Relative importance of the independent parameters on the decision of the optimal SC design.

the decision tree has an impact on the company's economy which is almost negligible in respect to the one that the optimal spare parts SC design (correct prediction) would imply. Hence, the low value of c makes it easier for managers and practitioners to accept the decisions suggested by the decision tree with $Dmax = 4$, even if the accuracy of the leaves is not very high. Meanwhile, in the Supplemental Material attached to this study, we also provide a second decision tree (with $Dmax = 15$), which guarantees more accurate predictions ($A = 97\%$), thus being useful for managers and practitioners to check the results of the DSS in Figure 6. We do not provide the decision tree with 100% accuracy (with $Dmax = 26$), but rather the tree on fifteen levels because, as reported by Morgan et al. (2003), a pruning reduces the overfitting problem, even if a slight reduction in the accuracy of the decision tree should be accepted.

The tree with $Dmax = 15$is less easy-to-use than the one with $Dmax = 4$, since fifteen concatenated questions should be answered before reaching a leaf, and the decision tree is split into several branches, making it difficult to identify the one relating to some specific input parameter conditions. For this reason, the Supplemental Material shows the decision tree with $Dmax =$ 15 not in graphical form but rather as a Python code. In this way, managers and practitioners can incorporate the script into their company systems, thus automating the process of answering questions and quickly achieving the optimal spare parts SC design. In the Supplemental Material, spare parts SC designs 1, 2, 3, 4, and 10 are the most frequently suggested, confirming the accuracy of the decision tree with $Dmax = 4$. Moreover, the decision tree with $Dmax = 15$ finds some specific cases where designs 5, 6, 7, 8, and 9 are economically profitable.

Overall, aiming to provide managers and practitioners with an easy-to-use and reliable DSS, the decision tree with $Dmax = 4$ is selected as the main tool to support the choice process. However, the benefits of the two alternatives (both the decision tree with $Dmax = 4$ and the one with $Dmax = 15$) can be reaped as follows, using the decision tree with $Dmax = 15$ only when the reliability of the tree with $Dmax = 4$ is not sufficient. At first, the DSS constituted by the decision tree with $Dmax = 4$ can be consulted to receive an initial suggestion on the optimal spare parts SC design. Then, managers and practitioners can check the accuracy of the leaf in which the SKU managed by their company falls. Hence, two circumstances can occur:

- If the accuracy of the considered leaf is high, the result of the easy-to-use decision tree with $Dmax = 4$ can be trusted.
- Conversely, if the accuracy of the leaf is low, then managers and practitioners can proceed as follows. First, they should check the KPI c and evaluate the increase of cost that they would have to pay in the case of a wrong decision. If they consider the increase of cost acceptable (it is often very low), then they can accept the decision tree prediction even if the accuracy is not very high. If, instead, they do not consider the increase of cost acceptable, they can then consult the decision tree with $Dmax = 15$ to get a more reliable result and be sure about the optimal spare parts SC design.

4.1. DSS application

The following case studies show the DSS application on the data provided by an Italian company which distributes bus spare parts to five main customers. Four DCs are currently available to stock more than 3,000 types of SKUs, and warehouse managers are in charge of the supply of items in each DC, for which they define the inventory control policies based on their algorithms and experience. The service level required by the company to meet customer requests for each spare part is equal to 95%. The company is an official partner of a well-known manufacturer of bus components, from whom it purchases all the stocks in the form of CM finished products (i.e. a single supplier serves all DCs). The company is recently considering performing a reconfiguration of its SC design, thus optimising the management of each SKU and the economic performance. Moreover, the company is interested in evaluating the possibility of buying AM spare parts instead of CM ones.

Here two case studies (A and B) are provided to illustrate different use cases of the DSS, referring to two different SKUs. For the selected SKUs, the lead-time (L_{AM}) and unitary cost (uc_{AM}) that the respective items would have if they were manufactured with AM were estimated by consulting AM experts from a company skilled in 3D printing. The results of both case studies are described below, showing: (i) the current SC design adopted by the company for the analysed SKU (AS-IS situation); (ii) the SC design recommended by the DSS; (iii) the SC design suggested by applying the mathematical model; (iv) the comparison of the previous information (i-iii) and a discussion on the results.

4.1.1. Case study A

Spare part A is an anti-particulate filter that is managed according to a hybrid SC design, where we can consider $Deg = 0.25$. Indeed, A-stocks are currently contained in three out of four DCs, since the remaining DC is small in size, and it is used to store only a few selected spare parts. The average demand of a customer for SKU A is 3 units/year and the cost of transporting one item from the DCs to a customer was estimated to be $etcentral = 225$ €/trip (based on the average distance between the DCs and the customers and the type of vehicle used for the deliveries, i.e. truck). Any stock-out of the warehouse for this SKU causes problems of unavailability to the customer's buses, which by law cannot travel without this filter. Therefore, the cost of a backorder was estimated at around 35,000 €/backorder in accordance with the company's staff. The average lead time (L_{CM}) guaranteed by the supplier for this SKU is 5 weeks, while the unitary purchase cost of this SKU (u_{CM}) is 1,057 €. On the other hand, L_{AM} and u_{AM}, were estimated to be 1.5 weeks and 1,370 €/unit, respectively.

Applying the decision tree with $Dmax = 4$ (DSS), the optimal SC design was identified as the number 4, corresponding to a hybrid configuration with $Deg = 0.25$ and CM spare parts. This choice was also confirmed by the mathematical model, which suggested as optimal the SC design characterised by $Deg = 0.25$, CM spares, and a total cost of around 37,000 €/year. Therefore, regarding the analysis of A-SKU, both the accuracy of the DSS (whose results matched those of the mathematical model), and the company choices (AS-IS situation) were validated.

4.1.2. Case study B

Spare part B is a specific type of connecting rod, currently managed according to an SC design of full centralisation ($Deg = 1$). Indeed, only one DC stocks inventory of B-items, serving the demand of all the customers. For SKU B, the average demand in the DC is equal to 5 units/year and the external transportation cost is still assumed equal to 225 €/trip. A stock-out of B-inventory causes problems of unavailability of the customer's vehicles. Hence, the cost of a backorder was estimated according to the know-how of the company's staff equal to $uback = 50{,}500$ €/backorder. The average lead time (L_{CM}) guaranteed by the supplier for this SKU is 4.5 weeks, while the unitary purchase cost of B (u_{CM}) is 594 €. Finally, L_{AM} and u_{AM} were estimated to be 2.5 weeks and 1,052 €/unit, respectively.

The decision tree with $Dmax = 4$ suggests as optimal the SC design 1 (that is $Deg = 0$ and AM spares). Such a prediction is characterised by a risk percentage of cost increase due to an incorrect prediction equal to 6%, which is considered too high by the company. Therefore, to obtain a more accurate result, the decision tree with $Dmax = 15$ was also consulted. This decision tree suggests 4 as the optimal SC design (hybrid centralisation of CM spare parts and $Deg = 0.25$). Applying the mathematical model, the same result was achieved, recommending the SC design with $Deg = 0.25$ and CM items, which has a total cost of 77,942 €/year. Hence, the mathematical model gave the same result as the decision tree with $Dmax = 15$ and the DSS was validated. Ultimately, the company's AS-IS policy was not confirmed by the results of the case study, showing that the firm should consider adopting a hybrid SC configuration (instead of a centralised one), thus allocating B-stocks in three out of four DCs. However, the analysis revealed that the company is justified in sourcing CM B-parts because, for such a SKU, AM technology is less cost-effective than the CM one.

5. Conclusions

This paper proposes a DSS to support managers and practitioners in deciding on the optimal spare parts SC design (i.e. the decision about the optimal spare parts SC configuration combined with the choice of the manufacturing technology). The developed DSS guides the decision between five different spare parts SC configurations (centralisation, decentralisation, and three hybrid configurations) where spare parts could be manufactured either in AM or in CM, thus considering a total of ten different spare parts SC designs. To develop such a DSS, four main steps were followed: (i) a novel mathematical model was developed for determining and comparing the total costs of the different spare parts SC designs (including the cost of purchasing spare parts from external suppliers, cost of placing replenishment orders, holding costs, outbound transportation costs, and backorder costs); (ii) the most relevant input parameters for the mathematical model were determined through the development of an ANOVA; (iii) an extensive parametric analysis was performed where 10,000 different spare parts SC scenarios were developed, assigning values to the most relevant input parameters of the mathematical model (through the Sobol quasi-random low discrepancy sequence) and, for each scenario, the optimal spare parts SC design was identified using the mathematical model mentioned in (i); (iv) the parametric analysis was used to feed a decision tree algorithm to obtain the aforementioned DSS. Based on a sensitivity analysis, the decision tree was pruned by imposing a maximum depth of four levels to ensure a trade-off between user-friendliness and accuracy of predictions and avoid overfitting. The results of the decision tree show that some leaves have high accuracy, while others not. However, the results prove that even when the accuracy of the leaves is low, the average percentage of cost increase that managers and practitioners should pay in the case of incorrect prediction is always less than 10% (often below 5%). Therefore, the DSS leads to a robust choice since it selects the optimal spare parts SC design or, in the case of a wrong prediction, it always ensures opting for a spare parts SC design that does not have a negative impact on business economies (implying a total cost similar to that of the correct prediction). Meanwhile, as an additional tool for improving the accuracy of the decision-making process, this study also provides a supplementary decision tree with a maximum depth of fifteen levels (Supplemental Material), which is less easy-to-use than the four-level tree but has higher accuracy ($A = 97\%$), allowing managers and practitioners to verify the DSS results when needed.

The DSS developed herein represents the main contribution of this study, since nothing similar has been done before. In fact, to the best of our knowledge, no tool supporting managers and practitioners in deciding the optimal spare part SC design (i.e. spare parts SC configuration and manufacturing technology) has been developed so far. A decision tree algorithm is chosen here to build the DSS since it is renowned as a rapid and easy-to-use tool (Arena et al. 2022; Sgarbossa et al. 2021) and it allows the robustness of decisions to be measured with proper KPIs. Moreover, we have chosen to develop the DSS by exploiting a machine learning algorithm and data mining techniques since these are particularly useful when there are many variables impacting the system (Morgan et al. 2003; Orrù et al. 2020).

The main findings of the present study can be summarised as follows:

- The developed DSS is based on six input parameters ($\#customers$, $\bar{D}_{1customer}$, $etcentral_i$, $uback$, uc_{AM}, and uc_{CM}), whose strong impact on the selection of the optimal spare parts SC design is demonstrated by the ANOVA. In contrast, the parameters L_{AM}, L_{CM}, and $ELTSL$ were found to be negligible concerning the decision process investigated.
- The DSS is provided in the form of a decision tree with a maximum depth of four levels. Given the large number of parameters (six) impacting the choice of the optimal spare parts SC design, such a tree has a total accuracy of 77%. However, it guarantees to identify the spare parts SC design with the minimum cost or, in the case of a wrong prediction, a solution that deviates from the minimum cost by less than 10% (often less than 5%). Meanwhile, if this four-level decision tree is not considered sufficiently reliable as a DSS, the use of such a tree can be combined with that of a more complex and more reliable one (with fifteen levels), consulting this second tree only when the KPIs a (leaf accuracy) and c (cost increase due to incorrect prediction) of the four-level tree are low and high, respectively. The fifteen-level decision tree is provided here in the form of a Python code instead of a graphical diagram representation so that managers and practitioners can easily implement it in their company systems, thus automating its consultation.
- The spare parts SC designs most frequently suggested by the DSS are those with $Deg_i = 0.25$ (designs 3 and 4), proving the importance of considering hybrid SC configurations in the analysis instead of focusing only on centralised and decentralised spare parts SC configurations. On the contrary, spare parts SC designs 5–9 are profitable only in very specific cases that the four-level tree does not consider.

It is worth noting that the results achieved are strictly related to spare parts SCs where the following assumptions can be considered valid: the spare parts demand follows a Poisson distribution, lead times are deterministic, warehouses have unlimited capacities, DCs are managed with (s,Q) inventory policy, and lateral transhipments, environmental impacts, reverse logistics, and spare parts obsolescence can be neglected. Besides, it is important to remember that the proposed DSS aims at optimising the allocation of individual SKUs considering only the variable costs of two-echelon SCs. However, all the mathematical formulas used to calculate the total costs of SC designs are reported in the present study. For this reason, if managers and practitioners do not consider the aforementioned simplifying assumptions compatible with the reality of their company, this problem can be overcome. In fact, although managers and practitioners cannot exploit the results of the DSS, they can be supported in their decisions by using the mathematical model herein provided and introduce or remove proper constraints, thus evaluating the real situation of their companies. For example, the assumption of decentralised DCs equidistant to the end customers can be easily removed by using the mathematical formulas of Section 3.1 and associating each DC with the specific transport cost calculated based on the exact distance that separates that DC from its end customer.

5.1. Theoretical and practical contributions

An efficient spare parts SC configuration improves the performance of a company in terms of economy, sustainability, and service level. Despite the importance of optimising the SC configuration, up to now, the problem of choosing between centralisation, decentralisation, and hybrid configurations has been overlooked in the literature. Specifically, the lack of quantitative methods to compare different SC configurations has led many spare parts dealers to optimise their SCs configurations based on their experience rather than on structured methods. Besides, recently, consideration has been given to the possibility of producing spare parts via AM, rather than CM, since AM technology can be more convenient under specific conditions. However, the decision on the optimal spare parts manufacturing technology has been hard to take for managers and practitioners since the existing literature lacks methods to quantitatively capture the differences between CM and AM SCs, providing evidence on when the adoption of AM spare parts can guarantee higher performance than the CM ones. In this context, the theoretical contribution of this paper is to overcome both these issues by providing a DSS and a mathematical model to understand under which conditions it is economically advantageous to have a centralised, decentralised, or hybrid SC configuration, also selecting the optimal manufacturing technology (AM or CM spare parts). As a corollary, the present work also lays the foundation for deeper scientific research regarding both the choice of the most cost-effective spare parts SC configuration (among centralisation, decentralisation, and hybrid SCs) and the choice between AM and CM spare parts.

At a practical level, the contribution of this study is to provide companies with a quick and user-friendly system (the DSS) for determining how to design spare parts SCs. The results of this study will help managers and practitioners in optimising for each SKU two aspects at the same time: the allocation of stocks inside company warehouses (choosing between centralisation, decentralisation, and hybrid configuration) and the items' manufacturing technology (AM or CM).

An example of how managers and practitioners can benefit from the results of this study is the following. Considering the company's most critical SKUs, by establishing their optimal SC design through the proposed DSS (consulting the 4-depth decision tree once for each SKU), managers and practitioners can rapidly compare their actual SC management policy with the ideal situation recommended by the DSS. In case of discrepancies between the current policies and the optimal situation suggested by the DSS, managers and practitioners can change the management of spare parts within the SC. Hence, immediate economic benefits with a limited effort can be obtained, since the company can first check only its critical spare parts (for example those in class A of an ABC analysis), and then verify the other SKUs in a second moment. Moreover, only four questions need to be answered to compare the current company situation with the optimal SC design suggested by the decision tree.

5.2. Future research developments

Future developments of this research could be threefold: first, to repeat the study considering companies which produce spare parts internally, instead of purchasing them from external suppliers. Second, to optimise SC designs considering multiple SKUs instead of individual SKUs, thus introducing fixed costs (i.e. economic investments in facilities and assets such as AM printers) in the analysis. Finally, to consider using Random Forest instead of a decision tree algorithm to interpret the results of the Sobol-based parametric analysis, thus making the machine learning training more accurate and minimising overfitting issues.

In addition to this, some assumptions underlying the mathematical model could be relaxed or eliminated in future works. For instance, lead times could be considered stochastic instead of deterministic, obsolescence costs of spare parts could be considered as separate costs instead of being included in the holding cost rate, and sustainability issues could be included in the analysis. Moreover, the possibility to distribute multiple spare parts during each transportation could be considered, as well as the facilities capacity constraints.

6. Data availability statement

The authors confirm that the data supporting the findings of this study are available within the article [and/or] its supplementary material.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Appendix A

The unitary transportation cost in hybrid or decentralised SC configurations (*etdecentral* in Equation (17)) depends on the unitary transportation cost in centralised SC configurations (*etcentral*). Indeed, in centralised configurations, the only DC is typically in a central location concerning the population of customers to be served. On the contrary, in hybrid or decentralised configurations, each of the several DCs is positioned close to its specific customers. Consequently (as aforementioned in Section 1), hybrid and decentralised SC configurations imply travelling shorter distances to distribute spare parts, thus leading to lower transportation costs than in centralised configurations. Therefore, the relationship between the unitary transportation cost in hybrid or decentralised SC configurations (*etdecentral*) and the unitary transportation cost in centralised SC configurations (*etcentral*) follows Equation A1.

$$et\ decentral = \ et\ central * f(Deg) \tag{A1}$$

To determine the function $f(Deg)$ the following procedure was followed. Eight case studies related to eight different SCs with eight different SKUs were selected from the literature (Ivanov 2021; Liu et al. 2014). For each case study, the data on demand, the number of customers, and geographical location of customers were collected and entered into the Anylogistix simulation software. Based on these data, Green Field Analyses (GFAs) were conducted to determine how transportation costs decrease when reducing the degree of centralisation. Specifically, several GFAs were run for each case study, gradually increasing the number of DCs imposed (starting from one and covering the whole range of possible SC configurations, from centralised to decentralised and passing by hybrid SC configurations), and the respective transportation costs were then calculated. For example, in a case study with ten customers, the number of DCs was varied from one to ten (with increments of one) and the respective transportation costs were identified. The results of all case studies were graphed (Figure A1), putting on the x-axis *Deg*, while on the y-axis the normalised transportation cost (that is, for each case study, the ratio $\frac{et}{etcentral}$).

Finally, interpolating the curve, it was possible to determine $f(Deg)$ (Equation A2).

$$f(Deg) = 0.7644 * Deg^2 + 0.2009 * Deg + 0.0161 \tag{A2}$$

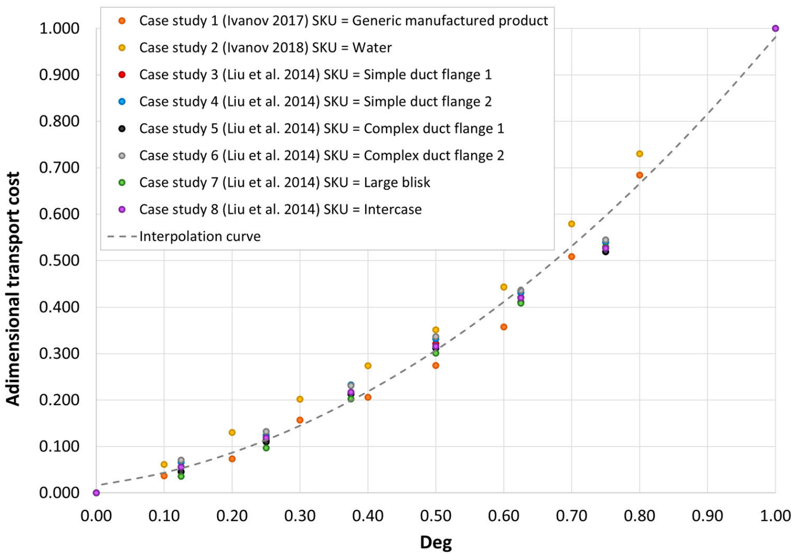

Figure A1. Relationship between centralised and decentralised transportation costs.

On the impact of additive manufacturing on the review of spare parts supply chains configuration: a decision support system

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Abstract: A well-configured spare parts supply chain (SC) improves the performance of spare parts retailers. Due to spare parts' demand volatility, the SC configuration should not be optimised only once, but reviewed during time. Particularly, reviewing the stock deployment policies associated with spare parts is fundamental. Therefore, structured methodologies should be adopted to choose between centralised, decentralised, or hybrid stock deployment policies. These methodologies should also determine the optimal spare parts manufacturing technology, since producing in-house additive manufactured (AM) spare parts (installing 3D printers inside distribution centres) rather than purchasing conventionally manufactured (CM) spare parts from suppliers affects the convenience of different stock deployment policies. However, literature overlooks structured methodologies to optimise stock deployment policies, and it is also unclear when a switchover from CM to AM spare parts is beneficial for spare parts retailers. To fill this gap, this paper provides a decision support system (DSS) to define the optimal stock deployment policies and manufacturing technologies to be adopted for spare parts. The DSS is a user-friendly decision tree, which allows evaluating the total costs of SCs characterised by different degrees of inventory centralisation, comparing, for the first time, the purchase of CM spare parts with the AM in-house production.

Keywords: supply chain configuration review; spare parts; additive manufacturing; decision support system (DSS).

1. Introduction

A well-configured spare parts supply chain (SC) reduces costs and enhances the competitiveness of spare parts retailers, resulting in a key factor to be pursued (Esmaeili et al., 2021). However, due to the intrinsic characteristics of spare parts (e.g., demand unpredictability and high expected service level), optimally configuring spare parts SCs is a tough task, where two challenges arise. First, the SC total costs should be minimised by reducing spare parts inventories inside distribution centres (DCs), while ensuring high service levels, but this is not straightforward since many cost items with opposite behaviour have to be balanced (e.g., holding, ordering, transporting, backorder costs, etc.) (Jiang et al., 2019; Mehrpouya et al., 2022). Second, to face demand volatility, the SC configuration cannot be optimised only once (when the business is born), but it should be reviewed during the business lifetime, perpetuating the SC optimisation, and maintaining an alignment between logistic activities and customer needs (Eldem et al., 2022; Mangiaracina et al., 2015).

Among the decisions to be made when reviewing a spare parts SC configuration, defining the optimal stock deployment policy for each individual Stock Keeping Unit (SKU) is of primary importance (Manikas et al., 2019). This activity implies choosing how to allocate each SKU to different DCs, opting for centralised, decentralised, or hybrid stock deployment policies (Pour et al., 2016). In decentralised stock deployment policies, spare parts are stored in multiple DCs, each serving a local customer, thus achieving SC flexibility, responsiveness, and reduced delivery times, but entailing high holding and facility costs since multiple DCs are managed (Holmström et al., 2010). Conversely, in centralised stock deployment policies, spare parts are stored in a single central DC which serves all the customers, thus reducing holding and facility costs (because of the risk-pooling effect), but implying longer delivery times, less SC flexibility, and less responsiveness (Frandsen et al., 2020). Finally, hybrid stock deployment policies can be selected, opting for intermediate solutions between centralised and decentralised stock deployment policies, thus achieving trade-off advantages (Cantini et al., 2021). Given the antithetical benefits of different stock deployment policies, choosing the optimal one for each SKU has been recognised as both a challenge and a strategic opportunity for spare parts retailers (Milewski, 2020; Daskin et al., 2022).

This challenge has been further complicated by the advent of additive manufacturing (AM) (Ahmed et al., 2022; Li et al., 2019). Such an emerging technology, in fact, has highly attracted the interest of spare parts retailers due to the possibility of producing spare parts close to the point of use (even inside DCs in the so-called "in-house production"). The in-house production, in fact, allows reducing the dependency on suppliers, procurement lead times, and inventory levels, disrupting the characteristics of SCs with respect to Conventional Manufacturing (CM) (Mashhadi et al., 2015; Waterman and Dickens, 1994). Therefore, when reviewing the configuration of existing spare parts SCs, spare parts retailers have also to decide on the manufacturing technology to be adopted for each SKU (AM or CM) since this choice affects the decisions on stock deployment policies (Ahmed et al., 2022). However, this is not straightforward: if on the one hand, spare parts retailers would want to fully exploit the benefits of AM by decentralising their stock deployment and producing spare parts directly within DCs (in-house production), on the other hand, this would entail huge investments due to the high costs of AM machines (a.k.a. 3D printers). Due to the complexity of this task, spare parts retailers require a structured methodology that supports them in reviewing what we will refer to as "SC design", namely the combination of both manufacturing technologies and stock deployment policies adopted for individual SKUs (Trancoso et al., 2018). More in detail, as stated by Basto et al. (2019), the aforementioned structured methodology needs to consider all available SKUs, adopting a multi-item perspective, and minimising the SC total costs (which includes the costs of producing or purchasing spare parts, the inventory holding costs, the ordering costs for replenishing DCs, the transportation costs for delivering spare parts, the backorder costs, and the costs of installing 3D printers). Moreover, according to the same authors (Basto et al., 2019), the structured methodology has to be quick-to-use and user-friendly for two reasons. First, to enable spare parts retailers to regularly review their SC design in an easy and fast way, without resulting time-consuming. Second, to allow the adoption of the proposed methodology in real companies, where advanced IT systems and highly skilled employees may lack.

Nevertheless, despite its importance, to the best of the authors' knowledge, such a structured methodology is currently missing. Indeed, the methodology by Cantini et al. (2022) is the only one that provides a quick and user-friendly decision support system (DSS) to help spare parts retailers in reviewing the design of existing SCs, but it presents some limitations. For instance, it does not consider the possibility to adopt AM in-house production of spare parts, which instead holds the true potential of AM technologies. Moreover, it adopts a single-item perspective and not a multi-item one (since the manufacturing technology and stock deployment policy of a single SKU per time is reviewed). However, this hampers spare parts retailers with many SKUs from understanding whether the reviewed SC design is single-sourced (with all CM or all AM spare parts), or dual-sourced with a mix of CM and AM spare parts. Finally, it does not consider investment costs, which are not negligible, especially considering the high costs of 3D printers. To fill this gap, this work aims at overcoming the limitations of Cantini et al. (2022) by developing a structured methodology (specifically a DSS in the form of a decision tree) that supports spare parts retailers in reviewing the design of existing SCs. Specifically, the proposed DSS considers the AM in-house production of spare parts, adopts a multi-item perspective, and includes the investment costs for purchasing 3D printers. Hence, considering multiple SKUs at the same time, it will suggest both their optimal stock deployment policies (i.e., centralised, decentralised, or hybrid stock deployment policies), and their optimal manufacturing technologies, determining whether to produce all SKUs in-house with AM, to purchase all of them as CM finished products from suppliers, or to adopt a dual-sourcing strategy, where some SKUs are produced in-house with AM and some are purchased as CM from suppliers.

The reminder of the present paper is as follows. Section 2 presents the relevant background literature on the design of SCs with AM spare parts (to deepen and confirm the aforementioned literature gaps). Section 3 describes the problem addressed in this work together with its simplifying assumptions. Section 4 presents the methodological framework followed to develop the DSS. Section 5 discusses the DSS results, also showing its application on a case study. Finally, Section 6 provides some conclusions, proposing future work developments.

2. Literature review

As mentioned in the introduction, spare parts retailers are lacking a quick and user-friendly structured methodology that supports them in reviewing the design of existing SCs, especially when AM is involved (Yazdekhasti et al., 2022). Literature, in fact, is lacking in this perspective since research on AM in spare parts SCs is still scarce and in its preliminary stage (Xu et al., 2021). According to Kunovjanek et al. (2020), most of the existing research on AM is on material science and mechanical engineering areas, while studies on how the adoption of AM impacts spare parts SCs and, particularly, the optimal stock deployment policies are very limited and mainly qualitative. For instance, Pour et al. (2016) have proposed a comparative study to describe the benefits achieved by producing AM spare parts in specific cases of centralised and decentralised stock deployment policies, while Holmström et al. (2010) have proposed a conceptual approach to introduce AM in spare parts SCs. However, according to Khajavi et al. (2014), quantitative analyses are of paramount importance to encourage spare parts retailers in reviewing the design of existing SCs, and an economic evaluation of the SC total cost is necessary to identify the optimal stock deployment policies and manufacturing technologies. In this perspective, some quantitative analyses have been developed to select the most cost-effective stock deployment policies of AM spare parts, but they only focus on AM, without comparing it with CM (Knofius et al., 2021). For example, Liu et al. (2014) have proposed a SCOR model to measure the performance of an aircraft's spare parts SC in terms of reliability, responsiveness, agility, costs, and asset management, but they have focused only on AM. Similarly, also Ghadge et al. (2018) and Li et al. (2017) have considered only AM spare parts, adopting system dynamics simulations to compare the performance of centralised and decentralised stock deployment policies. However, these works propose exploratory studies and simulations, whose results are strongly case specific and concern SCs with a very simple structure (Xu et al., 2021). Whereas only a handful of quantitative studies can be found that are not case specific and quantitatively assess the impacts of AM in terms of SC total costs (Zhang et al., 2017), but again they do not offer a comparison with CM. For example, Emelogu et al. (2016) have proposed a stochastic cost model to quantify the cost-effectiveness of different stock deployment policies considering only AM spare parts, while Ashour Pour et al. (2019) have proposed an analytic approach based on Joint Economic Lot Sizing model to accomplish a similar task.

Nevertheless, a comparison between SCs with AM and CM spare parts is needed to determine how to review the SC design (Delic and Eyers, 2020), especially considering that most of SCs currently adopt CM as manufacturing technology, being interested in evaluating a switchover to AM (Westerweel et al., 2018). To the best of the authors' knowledge, however, there is only one study doing this (Cantini et al., 2022). This work provides a DSS based on a machine learning algorithm that supports spare parts retailers in reviewing the SC design by optimising, at the same time, the manufacturing technology, and the stock deployment policy of a single SKU. However, this work presents some limitations. First, it compares SCs where both AM and CM spare parts are purchased as finished products from suppliers, without investigating SCs where 3D printers are installed inside DCs (i.e., neglecting the AM in-house production). Consequently, no installation costs and capacity constraints of 3D printers are considered in the analysis, preventing spare parts retailers from defining the optimal number of 3D printers to be installed in each DC. Moreover, a single-item perspective is adopted, while instead a multi-item one is needed (Khajavi et al., 2014). Indeed, by focusing on a single SKU per time, spare parts retailers with many SKUs lose the overall SC picture, being hampered in understanding whether the reviewed SC design (obtained following the DSS suggestions) is single-sourced (whether with CM or AM spare parts), or dual-sourced with a mix of CM and AM spare parts.

This work aims to overcome the aforementioned limitations and fill the identified literature gap by developing a multi-item DSS that supports spare parts retailers in reviewing the design of existing SCs, evaluating the optimal manufacturing technologies and stock deployment policies associated with multiple SKUs. More details on the different manufacturing technologies and stock deployment policies considered in the DSS are provided in the next section.

3. Problem description and assumptions

3.1. Problem description

As discussed before, spare parts retailers predominantly adopt CM spare parts, purchasing them from suppliers, deciding their stock deployment policies, and delivering them from DC(s) to customers (Westerweel et al., 2018). However, due to the potentialities of AM, spare parts retailers are currently investigating the possibility of producing spare parts via AM, switching the manufacturing technology of either all or some SKUs, considering the effects of this change on the optimal stock deployment policies, and hence on the design of existing SCs. Based on this, we have decided to focus on the following problem.

We consider the case of a two-echelon SC, as suggested by Tapia-Ubeda et al. (2020), where spare parts retailers are currently purchasing multiple CM SKUs from suppliers, storing them into DC(s) based on their selected stock deployment policies, and delivering to multiple customers (to meet their demand). Concerning the stock deployment policies selected for CM spare parts, we assume that they have already been optimised, for instance by applying the methodology by Cantini et al. (2022). As we will better describe later (Section 4.1.1), this assumption does not represent a limitation. Given this starting condition (i.e., optimised stock deployment policies of CM spare parts), following Cantini et al. (2022), this means that spare parts can be managed according to five different stock deployment policies. These are distinguished based on the parameter "degree of centralisation" (Deg, Equation 1), which depends on the number of DCs ($\#DC$) set to fulfil the demand of customers (whose number is expressed as N). Specifically, these five different stock deployment policies range from centralised ($Deg = 1$) to decentralised ($Deg = 0$), crossing through three hybrid stock deployment policies (Deg equal to 0.25, 0.50, or 0.75), as depicted in Figure 1 considering an example company which serves six customers.

$$Deg = degree\ of\ centralisation = \begin{cases} 1 & centralised\ SC\ configuration \\ 1 - \frac{\#DC}{\mathrm{N}} & else \end{cases} \tag{1}$$

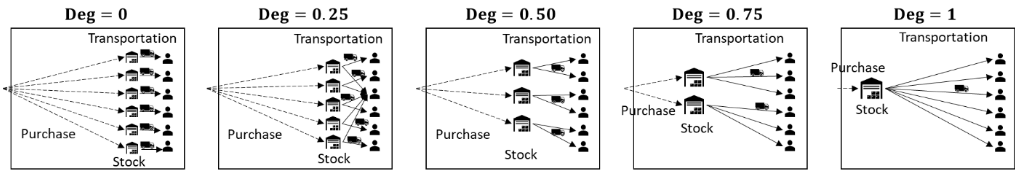

Figure 1. Investigated stock deployment policies in the example of a two-echelon SC with six customers. $Deg = 0$ *means decentralisation,* $Deg = 1$ *is centralisation, while the values in between are hybrid stock deployment policies.*

After having optimised the stock deployment policies of CM SKUs, spare parts retailers are able to divide them into different groups (which we will refer to as "sub-sets") based on their optimal Deg $(0, 0.25, 0.50, 0.75, 1)$. Therefore, each sub-set contains all CM SKUs characterised by the same Deg, as shown in Figure 2 (which considers the example of a company with five SKUs associated with three stock deployment policies). In this context, spare parts retailers are considered to perform the SC design review. Specifically, dividing SKUs into sub-sets, they are allowed to compare the sole optimal stock deployment policy associated with CM SKUs (characterising each sub-set) with different alternatives of stock deployment policies for AM SKUs. In this way, when reviewing the SC design, evaluation efforts are reduced since un-optimal stock deployment policies for CM SKUs are not considered. We are aware of the simplifications behind this choice (i.e., the SC design is not optimised by considering all SKUs together, but dividing them into sub-sets and looking for the optimum within each sub-set). However, we consider this choice acceptable for the following reason. Other authors (Daskin et al., 2002; Patriarca et al. 2016) have proposed exact optimisation models to optimise stock deployment policies in two-echelon SCs (focusing only on CM spare parts, without considering AM). However, the proposed exact optimisation models require Lagrangian relaxations, branch-and-bound algorithms, and heuristic forcing rules to be solved, leading to solutions which are local optimums (not necessarily absolute ones). Therefore, having to accept a local optimum solution in any case, we decided to simplify the problem from the very beginning, taking advantage of this simplification to achieve a quick and user-friendly SC design review.

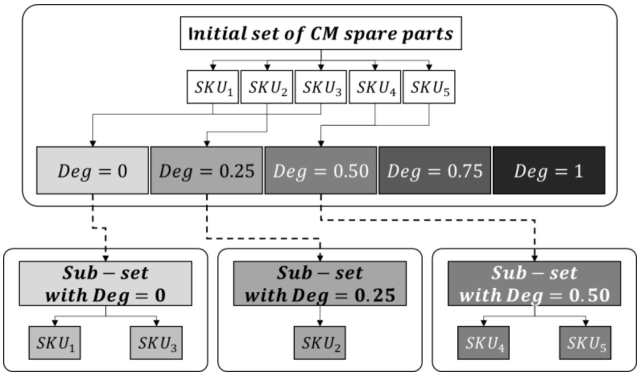

Figure 2. Example of how to split the initial CM SKUs into sub-sets.

At the time of the SC design review, we consider that spare parts retailers are interested in investigating the introduction of AM technologies in SCs. This means that, when reviewing the SC design, for each sub-set, spare parts retailers are considering substituting the purchase of CM spare parts from suppliers with the AM in-house production, as depicted in Figure 3. According to Figure 3, CM SKUs are considered to be purchased by suppliers, stored inside DC(s), and delivered to customers. Instead, after purchasing AM raw material and storing it inside DC(s), AM SKUs are considered produced via 3D printers (which are installed inside DC(s)), kept in stock, and delivered to customers. Customers may also be subsequent retailers, (Fathi et al., 2021).

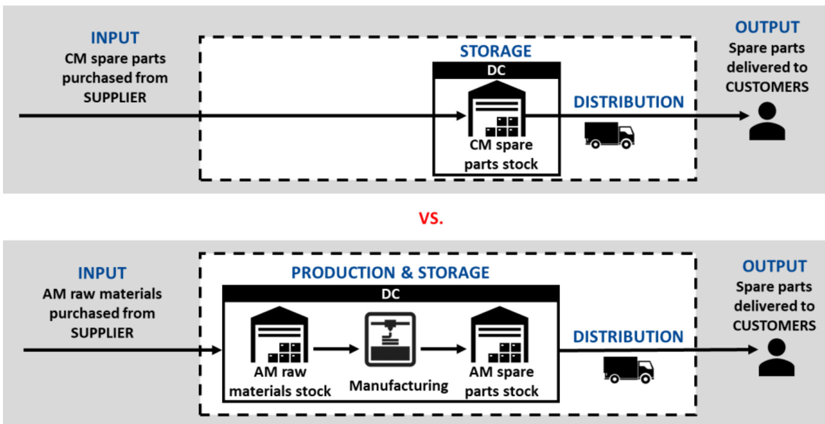

Figure 3. Control volumes (within dashed rectangles) considered according to the selected manufacturing technology. SKUs can be purchased as CM by suppliers (up) or produced in-house with AM (down).

In this context, per each sub-set, three options are available concerning the spare parts manufacturing technology, among which spare parts retailers have to choose: (i) to keep on purchasing from suppliers all SKUs as CM spare parts (to which we will refer as "single-sourcing CM"), (ii) to replace the purchase of CM spare parts with the AM in-house production (to which we will refer as "single-sourcing AM”), and (iii) to produce in-house with AM some SKUs, while purchasing in CM the others (to which we will refer as “dual-sourcing CM/AM”).

The choice about the spare parts manufacturing technologies is highly interconnected with the other main choice that spare parts retailers have to make when reviewing the SC design: the stock deployment policies (Li et al., 2017). In this regard, we consider that spare parts retailers can choose between the five stock deployment policies already described in Figure 1. This means that, for each sub-set of SKUs, spare parts retailers have now to choose between eleven SC designs, which result from the combination of five different stock deployment policies and three manufacturing technologies. The eleven SC designs are summarised in Figure 4 considering, as an example, the sub-set of CM SKUs with $Deg = 0$. Figure 4 can easily be extended to other sub-sets by considering different values of Deg for CM SKUs.

STARTING CONDITION: sub-set of SKUs purchased as CM spare parts and deployed with $Deg = 0$		**STOCK DEPLOYMENT POLICIES**				
		$Deg = 0$	$Deg = 0.25$	$Deg = 0.50$	$Deg = 0.75$	$Deg = 1$
MANUFACTURING TECHNOLOGIES	**Single-sourcing CM**	0 Keep on purchasing all SKUs as CM spare parts, and mantain the initial stock deployment policy characterising the sub-set (Deg=0)	-	-	-	-
	Single-sourcing AM	1 Produce all SKUs as AM spare parts, and mantain the initial stock deployment policy with Deg=0	2 Produce all SKUs as AM spare parts, and change the stock deployment policy adopting Deg=0.25	3 Produce all SKUs as AM spare parts, and change the stock deployment policy adopting Deg=0.50	4 Produce all SKUs as AM spare parts, and change the stock deployment policy adopting Deg=0.75	5 Produce all SKUs as AM spare parts, and change the stock deployment policy adopting Deg=1
	Dual-sourcing CM/AM	6 Produce some SKUs with AM, adopting Deg=0 as stock deployment policy. Keep on purchasing the other SKUs as CM spare parts, mantaining the initial stock deployment policy (Deg=0)	7 Produce some SKUs with AM, adopting Deg=0.25 as stock deployment policy. Keep on purchasing the other SKUs as CM spare parts, mantaining the initial stock deployment policy (Deg=0)	8 Produce some SKUs with AM, adopting Deg=0.50 as stock deployment policy. Keep on purchasing the other SKUs as CM spare parts, mantaining the initial stock deployment policy (Deg=0)	9 Produce some SKUs with AM, adopting Deg=0.75 as stock deployment policy. Keep on purchasing the other SKUs as CM spare parts, mantaining the initial stock deployment policy (Deg=0)	10 Produce some SKUs with AM, adopting Deg=1 as stock deployment policy. Keep on purchasing the other SKUs as CM spare parts, mantaining the initial stock deployment policy (Deg=0)

Figure 4. SC designs investigated by considering different manufacturing technologies and stock deployment policies. This figure refers to sub-set of SKUs with Deg = 0. However, it can be extended to other sub-sets moving to the right the SC design number zero.

In this work, we will focus on developing a structured methodology to support spare parts retailers in addressing the problem described above. Specifically, we will develop a DSS (in the form of a decision tree) that will guide spare parts retailers in defining, in a quick and user-friendly way, the most cost-effective SC design to adopt (among those described in Figure 4). The DSS has been developed following a three-steps methodological framework, which is described in Section 4. However, before describing the methodological framework, the assumptions on which it relies are listed in the following sub-section.

3.2. Assumptions

The simplifying assumptions underlying this study are described below, reporting the scientific contributions on which they are based. These assumptions are considered valid since this study aims to support spare parts retailers in making strategic (not tactical or operational) decisions on the optimal SC design.

1. No capacity constraints are considered for supplier's warehouse and DCs (Tapia-Ubeda et al., 2020).
2. Customer demand for spare parts is assumed stochastic with a Poisson distribution, while the supplier procurement lead time is assumed deterministic and dependant only on the product (SKU or AM raw material), not on the geographical location of DCs (Lolli et al., 2022).
3. All DCs in an SC design are considered characterised by the same average transportation costs (Cantini et al., 2022). Moreover, transportation costs are calculated by assuming that only one spare part is distributed in each trip since a Poisson demand is considered, which is known as law of rare events.
4. The period considered to develop this analysis is one year (Daskin et al., 2002).
5. A continuous (ROP, Q) inventory policy is used to manage stocks of spare parts (Fathi et al., 2021; Ivanov, 2021; Sapna Isotupa, 2006) and AM raw materials (Song and Zhang, 2020), where ROP is the reorder point and Q is the optimal order quantity.
6. Both the purchase of CM spare parts and the production of AM ones are performed according to a make-to-stock policy (Jiang et al., 2017; Kumbhar and Mulay, 2018). Conversely, the on-demand production of AM spare parts is precluded, being theoretically advantageous but not applicable in real companies due to current AM technological limits (high production times) (Liu and Shin, 2019; Sgarbossa et al., 2021).
7. No sustainability aspects and risks affecting different SC designs are considered, excluding reverse logistics, environmental impacts of SC designs, lateral transhipments, and risks connected to the protection of intellectual property rights and liability of CAD projects (Zijm et al., 2019).
8. All AM SKUs are considered made of the same AM raw material (Mehrpouya et al., 2022; Priarone et al., 2021).
9. SKUs are supposed producible with both AM and CM (Chaudhuri et al., 2021).
10. Finally, since we are focusing on reviewing the design of existing SCs, fixed investment costs for purchasing/renting facilities are not considered since we assume that the DCs are already owned by spare parts retailers. Therefore, we only consider facilities variable costs.

4. Methodological framework

Considering spare parts retailers who manage CM SKUs as described before (having already optimised their stock deployment policies and having divided SKUs into sub-sets), in this work, for each sub-set, we propose a DSS to support spare parts retailers in reviewing the SC design. Specifically, to develop the DSS (one for each sub-set) a methodological framework composed of three steps was followed. In Step i, we developed a heuristic model that was used to determine the most cost-effective SC design among the eleven alternatives in Figure 4, considering a multi-item perspective, which means reviewing, at the same time, the SC design of all SKUs in the sub-set. In Step ii, we carried out a parametric analysis to investigate the use of the heuristic model on a sample of 1,000,000 realistic scenarios (i.e., spare parts SCs with different numbers of customers and SKUs, where each SKU is characterised by different demand, purchasing costs, transportation costs, backorder costs, required service level, etc.). Finally, in Step iii, the DSS was obtained by leveraging a machine learning algorithm (specifically a decision tree algorithm) fed with the results of the parametric analysis. Each step is described below in a specific section.

4.1. Step i – Heuristic model

In Step i, a heuristic model was developed to review the design of existing SCs, selecting the most cost-effective alternative among those reported in Figure 4, and adopting a multi-item perspective. The heuristic model depends on the indexes, input parameters, and variables listed in Table 1. Moreover, it follows a similar logic of the relax and fix optimisation method by Friske et al. (2022), where the general problem is split into small sub-problems, nested iterative loops are built, and a specific subproblem is solved to optimality in each iterative loop. Specifically, after a preliminary **initialisation**, the proposed heuristic model is based on three nested iterative loops: an **inner loop**, an **intermediate loop**, and an **outer loop**. The initialisation involves setting adequate starting conditions, which implies ensuring that the initial stock deployment policies of CM spare parts are optimised, splitting the CM SKUs into sub-sets, and focusing on a specific sub-set, where proper initial values are assigned to some parameters to begin the loop iterations. Subsequently, for each SKU in the considered sub-set, the inner loop selects, the optimal manufacturing technology (CM or AM). Next, the intermediate loop determines the number of 3D printers required to meet the production of AM spare parts. Finally, the outer loop suggests the optimal stock deployment policies, completing the SC design review.

Table 1. Indexes, input parameters, and variables of the heuristic model.

Index	Description	Unit of measure
$\boldsymbol{i}$	Identifier of the considered SC design. i assumes integer values between 0 and 10 according to Figure 4	-
$\boldsymbol{d}$	Considered DC. Given the analysed type of SC design (CM, AM, or CM/AM), d assumes integer values between 1 and $\#DC_{CM}$ or $\#DC_{AM}$	-
$\boldsymbol{j}$	Manufacturing technology of each SKU. j can be CM or AM	-
$\boldsymbol{k}$	Considered SKU. k assumes integer values between 1 and K	-
Input parameter	**Description**	**Unit of measure**
$\boldsymbol{K}$	Total number of SKUs in the considered sub-set	-
$\boldsymbol{N}$	Number of customers served by the spare part retailer	-
$\boldsymbol{\bar{D}_{1c_k}}$	Average annual demand emitted by one customer for each SKU	units/time
$\boldsymbol{Deg_{CM}}$	Degree of centralisation of CM spare parts. It can assume specific values according to Figure 1	-

$\boldsymbol{Deg_{AM}}$	Degree of centralisation of AM spare parts. It can take specific values according to Figure 1	-
$\boldsymbol{t\ central}$	Unitary transportation cost to deliver an SKU from the central DC ($Deg_{CM} = 1$ or $Deg_{AM} = 1$) to a customer	€/transportation
$\boldsymbol{c_{b_k}}$	Unitary backorder cost of each SKU	€/backorder
$\boldsymbol{L_k}$	Procurement lead time required by supplier to deliver a CM SKU	time
$\boldsymbol{uc_k}$	Unitary purchase cost of a CM SKU. It includes all costs that the supplier incurs (e.g., production, quality tests, equipment, etc.) together with the desired profit margins (Pour et al., 2016)	€/unit
$\boldsymbol{oc}$	Unitary cost of a supply order. It is given by the product between the average time required to issue one supply order and the hourly labour cost in DCs	€/order
$\boldsymbol{h_{\%_d}}$	Holding cost rate for keeping SKUs in a DC during the period of analysis. It includes variable costs of facilities, and risks connected to opportunity costs and stocks obsolescence (Khajavi et al., 2014)	$time^{-1}$
$\boldsymbol{n_k}$	Constant which, multiplied by the purchase cost of a CM SKU, returns the production cost of an equivalent AM SKU (Knofius et al., 2021)	-
$\boldsymbol{L_{raw}}$	Procurement lead time required by supplier to deliver AM raw material	time
$\boldsymbol{SL}$	Desired spare parts service level. It is the same for all SKUs, being the ratio between the number of demands answered on time for each SKU and the total number of demands answered for that SKU (Ivanov, 2021)	-
$\boldsymbol{SL_{raw}}$	Desired service level for AM raw material	-
$\boldsymbol{den_{raw}}$	Density of AM raw material	Kg/m^3
$\boldsymbol{unit_{raw}}$	Unitary pack size according to which AM raw material is purchased (e.g., a metal can containing 20 kg of powder (Sandvik AB, 2022))	unit raw
$\boldsymbol{Cap_{3DP}}$	Average annual production capacity of a 3D printer. It is expressed in terms of production hours, being related to the opening time of DCs and the working hours of manpower (Basto et al., 2019)	time
$\boldsymbol{Leas}$	Annual leasing cost of a 3D printer. It is supposed to be bought on leasing to allow refurbishments when AM technology advances	€/time
Variable	**Description**	**Unit of measure**
$\boldsymbol{C_{tot_i}}$	Annual cost of a SC design	€/time
$\boldsymbol{C_{CM_{d,k}}}$	Annual cost of a CM SKU in a DC	€/time
$\boldsymbol{C_{AM_{d,k}}}$	Annual cost of an AM SKU in a DC	€/time
$\boldsymbol{C_{P_{d,k}}}$	Annual cost of purchasing a CM SKU (from the supplier), to replenish a DC	€/time
$\boldsymbol{C_{O_{d,k}}}$	Annual ordering cost for supplying a CM SKU in a DC	€/time
$\boldsymbol{C_{H_{d,k}}}$	Annual holding cost for keeping stocks of a SKU in a DC	€/time
$\boldsymbol{C_{T_{d,k}}}$	Annual transportation cost for delivering a SKU to customers	€/time
$\boldsymbol{C_{B_{d,k}}}$	Annual backorder cost of a SKU in a DC	€/time
$\boldsymbol{C_{Praw_{d,k}}}$	Annual cost for purchasing the AM raw material needed to produce a specific AM SKU in a DC	€/time
$\boldsymbol{C_{Hraw_{d,k}}}$	Annual holding cost for keeping in a DC the specific quantity of AM raw material required to produce a SKU	€/time
$\boldsymbol{C_{Oraw_{d,k}}}$	Annual ordering cost for supplying the AM raw material which is required to produce a certain SKU in a DC	€/time
$\boldsymbol{C_{Prod_{d,k}}}$	Annual AM production cost in a DC. It includes costs for creating CAD projects, setting up 3D printers, keeping manpower, printing spare parts, and performing quality tests	€/time
$\boldsymbol{\#3DP_d}$	Number of 3D printers to be installed in each DC	-
$\boldsymbol{C_{print_d}}$	Annual leasing cost of 3D printer(s) installed in a DC	€/time
$\boldsymbol{C_{3DP_{d,k}}}$	Annual leasing cost of 3D printer(s) installed in a DC, where the cost has been allocated to each individual SKU	€/time
$\boldsymbol{F_d}$	Number of SKUs for which AM production is allowed at the current loop iteration. F can assume integer values between 0 and K, where in the first loop iteration $F = K$ (AM allowed for all SKUs), while in the next loop iterations F is reduced if, for some SKUs, AM appears not economically convenient in respect with CM	-
$\boldsymbol{\overline{D_{d,k}}}$	Average annual demand of the considered SKU in each DC	units

$\#DC_{CM}$	Number of DCs in which SKUs should be stored if they were purchased as CM spare parts	-
$\#DC_{AM}$	Number of DCs in which SKUs should be stored if they were produced as AM spare parts	-
oc	Unitary cost of issuing one supply order	€/order
$\#ord_{d,k}$	Average number of supply orders for each SKU in each DC	-
$Q_{d,k}$	Optimal order quantity to replenish SKUs in a DC	units
$SS_{d,k}$	Safety stocks of each SKU in a DC. It corresponds to the smallest value that compensates demand fluctuations during the procurement lead time and ensures the desired service level	units
$h_{d,k}$	Unitary holding cost for keeping stocks of spare parts in a DC	€/time
$\overline{Dlt_{d,k}}$	Demand for each SKU received during the procurement lead time	units
z_{raw}	If the demand for AM raw materials follows a normal distribution, SL_{raw} is associated with the service factor (z_{raw}) of the corresponding standardised normal distribution	-
$I_{d,k}$	Average inventory of each SKU in a DC	units
t_d	Unitary transportation cost in a DC	€/transportation
$t\ decentral_d$	Unitary transportation cost to deliver an SKU from a decentralised DC ($Deg_{CM} > 1$ or $Deg_{AM} > 1$) to a customer	€/transportation
$\#backorders_{d,k}$	Average number of backorders of a SKU in a DC	-
uc_{raw}	Unitary purchase cost of AM raw material required to produce each specific SKU	€/unit raw
$\overline{q_{raw_k}}$	Average quantity of AM raw material required to produce an AM SKU	units raw
vol_k	Volume of each SKU	m^3
$prod_k$	Unitary AM production cost of a SKU, which is an AM spare part	€/unit
$\#ord_{raw_{d,k}}$	Number of supply orders issued in a DC to replenish the specific quantity of AM raw material required to produce a SKU	orders
$\#ord_{TOT\ raw_d}$	Total number of supply orders issued for supplying AM raw material (required to produce all AM SKUs) in a DC	orders
$\overline{D_{raw_d}}$	Average amount of AM raw material required to produce all SKUs in a DC	units raw
Q_{raw_d}	Optimal order quantity adopted to replenish AM raw material in a DC	units raw
$h_{raw_{d,k}}$	Unitary holding cost for keeping stocks of AM raw material in a DC	€/time
$I_{raw_{d,k}}$	Average inventory of AM raw material determined by an AM SKU in a DC	units raw
I_{TOTraw_d}	Average inventory of AM raw material determined by all AM SKUs in a DC	units raw
SS_{raw_d}	Safety stocks of AM raw material required to compensate demand fluctuations and ensure the desired service level in a DC	units raw
$\overline{Dlt_{raw_d}}$	Demand for AM raw material received during the procurement lead time	units raw
$p.time_k$	Number of production hours that 3D printers work to produce one unit of each AM SKU	time/unit
$time_{tot_d}$	Total number of production hours required to produce all AM SKUs	time
$\overline{\overline{D}_{1c}}$	Arithmetic mean of the values assumed by $\overline{D}_{1c_k}$ for all SKUs	units/time
$\overline{c_b}$	Arithmetic mean of the values assumed by c_{b_k} for all SKUs	€/backorder
$\overline{L}$	Arithmetic mean of the values assumed by L_k for all SKUs	time
$\overline{n}$	Arithmetic mean of the values assumed by n_k for all SKUs	-
$\overline{uc}$	Arithmetic mean of the values assumed by uc_k for all SKUs	€/unit

Figure 5 schematically represents the heuristic model, whose nested iterative loops (i.e., inner loop, intermediate loop, and outer loop) will be described in detail in the next sub-sections.

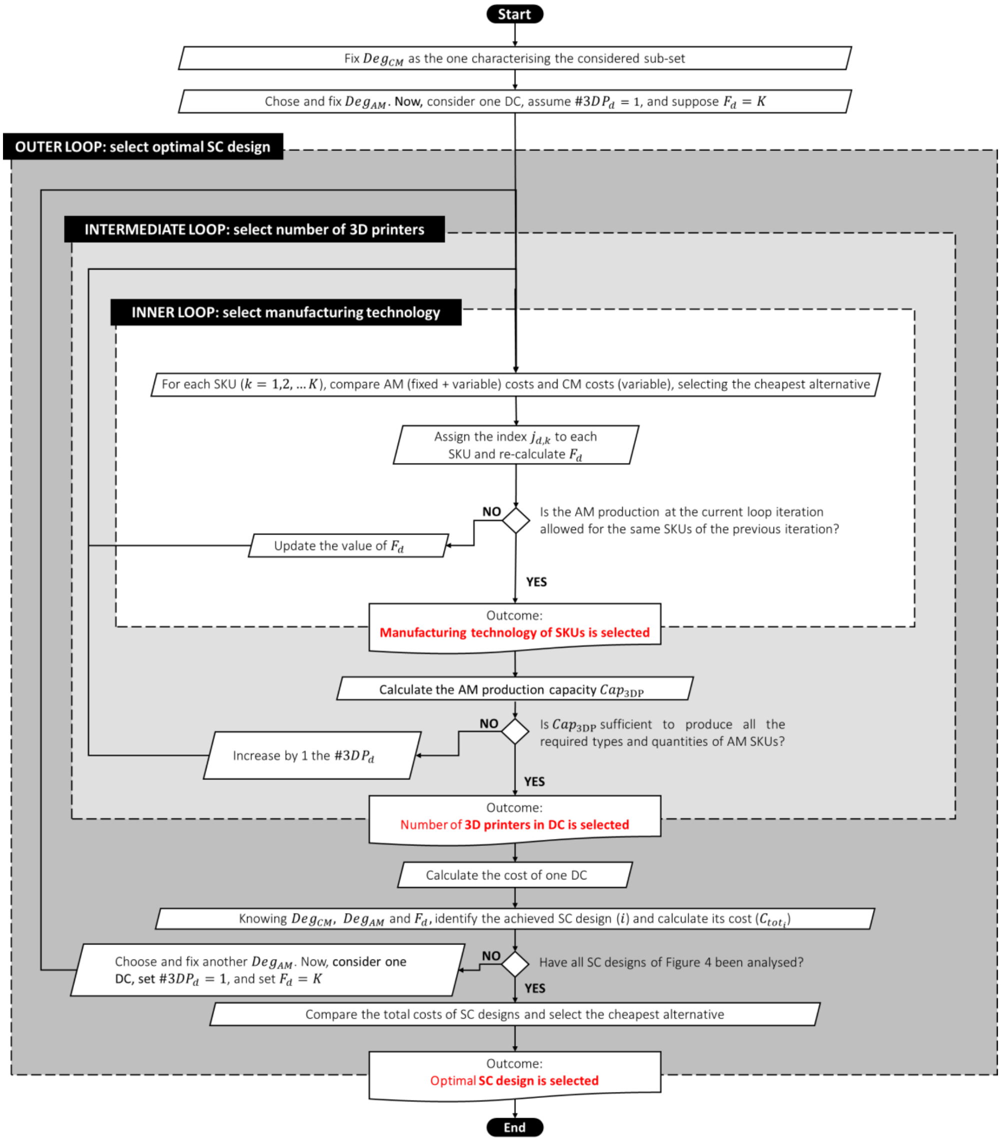

Figure 5. Schematic representation of the heuristic model.

4.1.1. Initialisation

To initialise the heuristic model, as already said, we consider spare parts retailers who have optimised stock deployment policies associated with CM spare parts, then dividing SKUs into sub-sets. However, if spare parts retailers have not yet accomplished this task, this is not a limitation since they can do so by consulting Appendix A. In fact, to enable any spare parts retailer achieving the required starting conditions, we applied the methodology by Cantini et al. (2022) focusing on CM spare parts (i.e., excluding AM variables). Hence, we derived Figure A.1, which guides the optimisation procedure, indicating under which conditions (combinations of input parameters listed in Table 1) each CM SKU has to be associated with different stock deployment policies.

Once optimised the stock deployment policies of CM spare parts, SKUs can be split into sub-sets, grouping together the SKUs associated with the same degree of centralisation Deg (from now on called Deg_{CM}, according to Table 1). At this point, a specific sub-set is considered, where the starting SC design of the related CM SKUs is known, and their common degree of centralisation (Deg_{CM}) is fixed. Based on this, using Equation 2, the number of DCs in which SKUs should be stored if they were purchased as CM spare parts ($\#DC_{CM}$) is determined.

$$\#DC_{CM} = \begin{cases} [(1 - Deg_{CM}) * N]^{+} \; if \; Deg_{CM} < 1 \\ 1 \qquad\qquad\qquad\qquad\quad if Deg_{CM} = 1 \end{cases} \tag{2}$$

Next, to compare the purchase of CM spare parts with the AM production, a certain value of Deg_{AM} is chosen and fixed (selecting one of the values allowed in Figure 1). Then, using Equation 3, the number of DCs ($\#DC_{AM}$) in which SKUs should be stored if they were produced in-house as AM spare parts is calculated.

$$\#DC_{\text{AM}} = \begin{cases} [(1 - Deg_{AM}) * N]^{+} \; if \; Deg_{AM} < 1 \\ 1 \qquad\qquad\qquad\qquad\quad if \; Deg_{AM} = 1 \end{cases} \tag{3}$$

At this point, the focus is put on a single DC, where, at the first inner loop iteration, a single 3D printer is considered installed ($\#3DP_d = 1$), and AM production is allowed for all SKUs ($F_d = K$).

4.1.2.Inner loop

In the inner loop, for each SKU falling into the considered sub-set, the optimal manufacturing technology (CM or AM) is selected. Specifically, in the first iteration of the inner loop, for each SKU we calculate and compare the total costs associated with the CM purchase in the considered DC (${C_{CM}}_{d,k}$) and the AM production (${C_{AM}}_{d,k}$), using Equations 4 and 5, respectively.

$${C_{CM}}_{d,k} = \left({C_P}_{d,k} + {C_O}_{d,k} + C_{H_{d,k}} + C_{T_{d,k}} + C_{B_{d,k}}\right) \tag{4}$$

$${C_{AM}}_{d,k} = \left(C_{Praw_{d,k}} + C_{Oraw_{d,k}} + C_{Hraw_{d,k}} + C_{Prod_{d,k}} + C_{H_{d,k}} + C_{T_{d,k}} + C_{B_{d,k}} + {C_{3DP}}_{d,k}\right) \tag{5}$$

More in detail, considering a SKU which is purchased by a supplier as a CM finished product, its total cost in a DC (${C_{CM}}_{d,k}$) is calculated by determining the cost items reported in Equation 4, where Deg_{CM} (characterising the investigated sub-set) is considered. Specifically, Equation 6 defines the total cost for purchasing CM spare parts, which depends on the customer demand for such a SKU (Equation 7). Equations 8-9 determine the total ordering cost to supply stocks of the considered SKU in the DC, which, in turn, depends on the (ROP, Q) supply policy (Equation 10) and the unitary holding cost of DCs (Equation 11). Equation 12 calculates the total holding cost for the considered SKU, which is related to the average inventory in each DC (Equation 13) and the safety stocks (Equations 14-15). Equation 16 defines the total transportation cost for delivering the considered SKU, which varies based on Deg_{CM}, as suggested by Cantini et al. (2022) in Equations 17-18. Finally, Equations 19-20 determine the total backorder cost related to the considered SKU.

$$C_{P_{d,k}} = uc_k * \overline{D_{d,k}} \tag{6}$$

$$\overline{D_{d,k}} = \left(\frac{\overline{D}_{1c_k} * N}{\#DC_{CM}}\right) \tag{7}$$

$$C_{O_{d,k}} = \left(oc * \#ord_{d,k}\right) \tag{8}$$

$$\#ord_{d,k} = \frac{\overline{D_{d,k}}}{Q_{d,k}} \tag{9}$$

$$Q_{d,k} = \sqrt{\frac{2 * \overline{D_{d,k}} * oc}{h_{d,k}}} \tag{10}$$

$$h_{d,k} = uc_k * h_{\%_d} \tag{11}$$

$$C_{H_{d,k}} = h_{d,k} * I_{d,k} \tag{12}$$

$$I_{d,k} = \frac{Q_{d,k}}{2} + SS_{d,k} \tag{13}$$

$$1 - \sum_{n=0}^{SS_{d,k}-1}\left[\frac{\left(\overline{Dlt_{d,k}}\right)^n}{n!} * e^{-\overline{Dlt_{d,k}}}\right] \geq (1 - SL) \tag{14}$$

$$\overline{Dlt_{d,k}} = \overline{D_{d,k}} * L_k \tag{15}$$

$$C_{T_{d,k}} = \left(t_d * \overline{D_{d,k}}\right) \tag{16}$$

$$t_d = \begin{cases} t\ decentral_d & if\ Deg_{CM} < 1 \\ t\ central & if\ Deg_{CM} = 1 \end{cases} \tag{17}$$

$$t\ decentral_d = t\ central * (0.7644 * Deg_{\mathrm{CM}}^2 + 0.2009 * Deg_{CM} + 0.0161) \tag{18}$$

$$C_{B_{d,k}} = (c_{b_k} * \#backorders_{d,k}) \tag{19}$$

$$\#backorders_{d,k} = \left[(1 - SL) * \overline{D_{d,k}}\right]^+ \tag{20}$$

Instead, concerning an individual AM SKU, the cost items composing its total cost in a single DC ($C_{AM_{d,k}}$, Equation 5) are calculated based on the fixed value of Deg_{AM} selected above. Specifically, Equation 21 defines the total cost for purchasing stocks of AM raw material, which is required to produce the specific SKU under analysis. Equation 21, in turn, depends on the customer demand for the SKU (Equation 22, which is like Equation 7, but for AM spare parts), the unitary purchase cost of AM raw material (Equation 23, suggested by Choudhury and Hashmi (2020) and Li et al. (2017)), and the average quantity of AM raw material needed to produce the considered SKU (Equation 24), which has the volume and the production cost determined by Equations 25 and 26, respectively, according to Sgarbossa (2021). Then, Equation 27 determines the total ordering cost for supplying the quantity of AM raw material which is required to produce the SKU under analysis. Equation 27, in turn, depends on the unitary cost of issuing one supply order, and the number of supply orders of AM raw material which are required to produce the considered SKU (Equation 28). Indeed, according to Song and Zhang (2020), the total raw material ordering cost (incurred to produce all AM SKUs in a DC) is assumed allocable to each SKU through weighted averages based on their respective raw material demand (Equations 29-30). It is worth mentioning that, as shown in Equation 29, the total ordering cost of AM raw material is calculated based on the quantities of AM raw material required to produce the only SKUs allowed to be produced with AM at the current loop iteration ($f = 1,2, \dots, F_d$). Moreover, the total ordering cost of AM raw material depends on the (ROP, Q) supply policy adopted for AM raw material (Equation 31, which is like Equation 10, but considering AM raw materials instead of CM finished products) and its unitary holding cost (Equation 32). Then, Equation 33 calculates the total holding cost for keeping stocks of AM raw materials, again allocating such a cost to each specific SKU (Equation 34) and considering the average inventory of AM raw material (Equation 35) and the safety stocks (Equations 36-37). Since the demand for AM raw materials does not necessarily follows a Poisson distribution, according to Syntetos and Boylan (2006) and the Italian National Standard (Italian Technical Commission for Maintenance, 2017), in Equations 36-37, safety stocks are calculated assuming a normal demand distribution when the total demand for AM raw materials received in the procurement lead time is higher than 15 units ($\overline{Dlt_{raw_d}} \geq 15$), while being a Poisson distribution in the opposite case ($\overline{Dlt_{raw_d}} < 15$). Next, Equation 38 defines the total cost for producing the considered AM SKU. Equations 12-13 are leveraged to define the total holding cost, like for CM SKU, but focusing on AM spare parts (using Deg_{AM} instead of Deg_{CM}). Equations 16, 39 and 40 determine the total transportation cost for delivering the considered SKU, which is calculated like in Equations 16-18, but using Deg_{AM}. Equations 19-20 are used to determine the total backorder cost related to the considered SKU, calculating such cost like for CM SKU, but using Deg_{AM}. Finally, Equations 41-42 define the total leasing cost of 3D printer(s) installed in the DC, allocating such a cost to the individual SKU through a weighted average based on the number of production hours that 3D printers work to produce the considered SKU (Equation 43, (Sgarbossa et al., 2021)) compared to the total number of production hours required to produce all AM SKUs (Equation 44).

$$C_{Praw_{d,k}} = uc_{raw_k} * \overline{q_{raw_k}} * \overline{D_{d,k}} \tag{21}$$

$$\overline{D_{d,k}} = \left(\frac{\overline{D}_{1c_k} * N}{\#DC_{AM}}\right) \tag{22}$$

$$uc_{raw} = \left(\sum_{k=1}^{K} vol_k * 10^3\right) * 20 \tag{23}$$

$$\overline{q_{raw_k}} = \frac{vol_k * den_{raw}}{unit_{raw}} \tag{24}$$

$$vol_k = \left(\frac{prod_k}{1.30}\right) * 10^{-6} \tag{25}$$

$$prod_k = n_k * uc_k \tag{26}$$

$$C_{Oraw_{d,k}} = oc * \#ord_{raw_{d,k}} \tag{27}$$

$$\#ord_{raw_{d,k}} = \frac{\#ord_{TOTraw_d} * (\overline{q_{raw_k}} * \overline{D_{d,k}})}{\overline{D_{raw_d}}} \tag{28}$$

$$\overline{D_{raw_d}} = \sum_{f=1}^{F_{d,j}} \left(\overline{q_{raw_f}} * \overline{D_{\iota,d,f}}\right) \tag{29}$$

$$\#ord_{TOTraw_d} = \frac{\overline{D_{raw_d}}}{Q_{raw_d}} \tag{30}$$

$$Q_{raw_d} = \sqrt{\frac{2 * \overline{D_{raw_d}} * oc}{h_{raw_d}}} \tag{31}$$

$$h_{raw_d} = uc_{raw} * h_{\%_d} \tag{32}$$

$$C_{Hraw_{d,k}} = h_{raw_d} * I_{raw_{d,k}} \tag{33}$$

$$I_{raw_{d,k}} = \frac{I_{TOTraw_d} * (\overline{q_{raw_k}} * \overline{D_{d,k}})}{\overline{D_{raw_d}}} \tag{34}$$

$$I_{TOTraw_d} = \left(\frac{Q_{raw_d}}{2} + SS_{raw_d}\right) \tag{35}$$

$$\begin{cases} 1 - \sum_{n=0}^{SS_{raw_d}-1} \left[\frac{\left(\overline{Dlt_{raw_d}}\right)^n}{n!} * e^{-\overline{Dlt_{raw_d}}}\right] \geq (1 - SL_{raw}) \; if\ Poisson\ demand \\ \left(z_{raw} * \sqrt{\overline{Dlt_{raw_d}} * L_{raw}}\right) if\ normal\ demand \end{cases} \tag{36}$$

$$\overline{Dlt_{raw_d}} = \overline{D_{raw_d}} * L_{raw} \tag{37}$$

$$C_{Prod_{d,k}} = prod_k * \overline{D_{d,k}} \tag{38}$$

$$t_d = \begin{cases} t\ decentral_d & if\ Deg_{AM} < 1 \\ t\ central & if\ Deg_{AM} = 1 \end{cases} \quad (39)$$

$$t\ decentral_d = t\ central * (0.7644 * Deg_{AM}^2 + 0.2009 * Deg_{AM} + 0.0161) \quad (40)$$

$$C_{3DP\,d,k} = C_{print_d} * \frac{\overline{D_{d,k}} * p.time_k}{time_{TOT\,d}} \quad (41)$$

$$C_{print_d} = Leas * \#3DP_d \quad (42)$$

$$p.time_k = \frac{prod_k}{1.30 * 0.00525 * 3600} \quad (43)$$

$$time_{TOT\,d} = \sum_{f=1}^{F_d} (p.time_f * \overline{D_{d,f}}) \quad (44)$$

At the end of the first iteration of the inner loop, for each SKU, $C_{AM\,d,k}$ is compared with $C_{CM\,d,k}$. Hence, the AM production is forbidden (being not economically convenient in respect with the purchase of CM finished products) if $C_{AM\,d,k}$ is higher than $C_{CM\,d,k}$. As a result, a value of the j-index is assigned to each SKU according to Equation 45, recommending the purchase of CM finished products for some SKUs, while allowing the AM production for the others.

$$j_{d,k} = \begin{cases} CM\ fixed\ (AM\ forbidden) & if\ C_{CM\,d,k} \le C_{AM\,d,k} \\ AM\ allowed & else \end{cases} \quad (45)$$

Based on this, the number of SKUs for which AM is allowed in the next loop iteration is recalculated according to Equation 46 (moving from F_d to F'_d, where the apostrophe indicates the update of the variable in the transition from a loop iteration to the next one).

$$F'_d = \sum_{k=1}^{K} f'_{d,k}\ where \begin{cases} f'_{d,k} = 1\ if\ j_{d,k} = AM \\ f'_{d,j,k} = 0\ if\ j_{d,k} = CM \end{cases} \quad (46)$$

Consequently, if the number of SKUs for which AM is allowed in the DC at the current loop iteration (F'_d) is lower than the same number at the previous iteration (F_d), this means that for some SKUs the CM purchase has been selected as the optimal manufacturing technology. In fact, by reducing the number of SKUs producible with AM, the cost of 3D printers allocated to each SKU ($C_{3DP\,d,k}$) increases, as well as $C_{Oraw_{d,k}}$ and $C_{Hraw_{d,k}}$. Therefore, $C_{AM\,d,k}$ can only increase over $C_{CM\,d,k}$ (which instead remains unchanged by not including fixed costs of 3D printers nor raw material costs). Hence, if $F'_d < F_d$, the cost-effectiveness of purchasing CM finished products over the AM production is confirmed. Meanwhile, unless $F'_d = 0$, for some SKUs the AM production is still allowed, requiring evaluating what is more convenient between AM and CM. Under these conditions ($F'_d \neq F_d$ and $F'_d \neq 0$), it is necessary to perform a new inner loop iteration, where, for each SKU, $C'_{CM\,d,k}$ is the same cost of the previous iteration ($C'_{CM\,d,k} = C_{CM\,d,k}$), while $C'_{AM\,d,k}$ is recalculated by applying

Equations 21-44 with the updated value of F'_d. In the new inner loop iteration, $C'_{CM\,d,k}$ and $C'_{AM\,d,k}$ are compared only for those SKUs for which $j_{d,k} \neq CM$. Indeed, if $j_{d,k} = CM$, only the cost $C'_{CM\,d,k}$ (which is equal to $C_{CM\,d,k}$) is considered, having fixed CM as the optimal manufacturing technology. When the current loop iteration is characterised by $F'_d = F_d$ or $F'_d = 0$, this means that, for each SKU, the optimal manufacturing technology ($j_{d,k}$) has been selected. Indeed, the solution of the current loop iteration is equal to the solution of the previous one ($j'_{d,k} = j_{d,k}$) and the convergence of the inner loop to the optimal solution is achieved (or the AM production has been forbidden for all SKUs, recommending to maintain the single-sourced SC design with CM spare parts with Deg_{CM}). Under these conditions, the inner loop is exited, moving to the intermediate one.

4.1.3. Intermediate loop

Once associated each SKU with the optimal manufacturing technology, the intermediate loop is used to assess if the production capacity of 3D printer(s) is sufficient to meet the demand of AM spare parts in the considered DC. To this end, the total production hours ($time_{TOT\,d}$) to be worked by 3D printers in the DC is determined, being the value assumed by Equation 44 in the last inner loop iteration. Then, knowing the number of 3D printers installed in the DC ($\#3DP_d$) and the capacity of each 3D printer (Cap_{3DP}), according to Equation 47, it is established whether the number of 3D printers is sufficient, or it has to be increased.

$$\#3DP'_d = \begin{cases} \#3DP_d \ \ if \ time_{TOT\,d} < (Cap_{3DP} * \#3DP_d) \\ \#3DP_d + 1 \ else \end{cases} \tag{47}$$

Finally, if $\#3DP'_d$ results higher than $\#3DP_d$ ($\#3DP'_d > \#3DP_d$), the whole inner loop must be executed again, but taking as the number of 3D printers the updated value $\#3DP'_d$ (instead of $\#3DP_d$). On the contrary, if $\#3DP'_d$ is equal to $\#3DP_d$ ($\#3DP'_d = \#3DP_d$), then the 3D printers installed in the DC are sufficient to satisfy the AM production. Therefore, the intermediate loop is exited, moving to the outer one.

4.1.4. Outer loop

Once the optimal production technology of each SKU is confirmed and the optimal number of 3D printers in each DC is known, the outer loop is used to calculate the total cost (C_{tot_i}) of the achieved SC design. To this end, first, the achieved SC design (i) is identified, assuming one of the values (0-10) reported in Figure 4. Specifically, i is equal to 0 if all SKUs are purchased as CM finished products ($F'_d = 0$). Conversely, i is a value included between 1 and 5 if all SKUs are produced with AM ($F'_d = K$), where the specific value of i depends on Deg_{AM} according to Figure 4. Finally, i assumes a value included between 6 and 10 if some SKUs are purchased as CM finished products, while producing with AM some others ($0 < F'_d < K$), where again the specific value of i depends on Deg_{AM}. Next, for the identified SC design, Equation 48 is used to calculate C_{tot_i}, summing the individual costs of

SKUs in DCs, by treating CM and AM spare parts based on the respective stock deployment policies (Deg_{CM} and Deg_{AM}).

$$C_{tot_i} = \sum_{d=1}^{\#DC_{CM}} \sum_{k=1, j_{d,k}=CM}^{K} C_{CM\,d,k} + \sum_{d=1}^{\#DC_{AM}} \sum_{k=1, j_{d,k}=AM}^{K} C_{AM\,d,k} \tag{48}$$

At this point, while keeping fixed Deg_{CM} (which characterises the considered sub-set), another value of Deg_{AM} is chosen and the application of the initialisation, inner, intermediate, and outer loops is repeated. After screening all possible values of Deg_{AM} (Figure 1), the respective optimal SC designs are reached, and their total cost is compared. Therefore, according to the objective function in Equation 49, the optimal SC design is selected as the one with minimum total cost.

$$min\left[C_{tot_i}\right] \; with \; i = 1,2, \dots, 10 \tag{49}$$

4.2. *Step ii - Parametric analysis*

Once built the heuristic model, in Step ii of the methodological framework, a parametric analysis was performed to test it on several realistic case studies, then using the results to feed and train a decision tree algorithm (achieving the final DSS). To this end, first, Sobol quasi-random values were associated with the input parameters of the heuristic model, collecting a sample of 1,000,000 realistic scenarios for each sub-set (i.e., spare parts SCs with different numbers of customers and SKUs, where each SKU is characterised by different demand, purchasing costs, transportation costs, backorder costs, required service level, etc.). Subsequently, each scenario was submitted to the heuristic model of Step i, determining its related optimal SC design ($i = 0 - 10$ in Figure 4). Finally, as the outcome of this parametric analysis, the dataset needed to feed and train the DSS was achieved for each sub-set, consisting of the 1,000,000 scenarios (highlighting for each scenario the set of values assumed by N, SL, $\overline{\overline{D_{1c}}}$, $t\ central$, $\bar{c_b}$, $\bar{L}$, K, $\bar{n}$, and $\overline{uc}$, which are described in Table 1) and the respective results of the heuristic model (identifiers i of the optimal SC designs).

Concerning the 1,000,000 scenarios investigated, as suggested by Bicchi et al. (2022), they were obtained by allowing the heuristic model's input parameters to assume uniformly distributed values according to the Sobol quasi-random low discrepancy sequence. The Sobol quasi-random low discrepancy sequence was used as sampling strategy since, when studying problems with numerous input parameters, it has been reported to better (more uniformly) cover the space of combinations of the admissible input parameter values in respect to other strategies (i.e., discrete sampling or Monte Carlo) (Burhenne et al., 2011). Hence, the value of each input parameter (par) was varied, according to Equation 50 (Bicchi et al., 2022), where Q is the total number of scenarios to be created, q is the specific scenario considered, M is the total number of heuristic model's input parameters, m is the specific input parameter to which we assign a Sobol value (par_{mq}), par_{ll} and par_{ul} are the lower and upper limits admitted for the value of the considered input parameter (Table 2), and S_{mq} is the Sobol sequence.

$$par_{mq} = par_{ll} + S_{mq} \cdot (par_{ul} - par_{ll})\ with\ m = 1, \dots, M\ and\ q = 1, \dots, Q \tag{50}$$

Table 2 summarises the ranges of admissible values considered for input parameters, where we excluded those which already had predefined values (Deg_{CM} and Deg_{AM}) and those for which a realistic fixed value was assumed by consulting the literature (Cantini et al., 2022; Sandvik AB, 2022; Vukkum et al., 2022) and a panel of experts in AM (oc, Cap_{3DP}, $Leas$, L_{raw}, $h_{\%_d}$, SL_{raw}, den_{raw}, and $unit_{raw}$, which were taken, respectively, equal to 5 €/order, 8 hours/day, 60,000 €/year, 2 weeks, 25%, 0.99, $7500\frac{Kg}{m^3}$, and a metal can containing $20\frac{Kg\ of\ steel\ powder}{can}$).

About Table 2, it is worth noting two considerations. First, each input parameter of Table 1 with subscript k was associated with specific Sobol values, allowing each SKU to assume different $\overline{D}_{1c_k}$, c_{b_k}, L_k, n_k, and uc_k. Second, by consulting Figure A.1 and following the indications by Cantini et al. (2022), the ranges of admissible values reported in Table 2 were properly updated respecting the conditions required to access the specific sub-set under analysis (i.e., specific combinations of input parameters N, SL, $\overline{D}_{1c_k}$, $t\ central$, c_{b_k}, L_k, K, n_k, and uc_k). For example, if a sub-set contains only SKUs which are demanded by less than 50 customers ($N < 50$), the range of variation of N was switched from 5÷100 (Table 2) to 5÷50, modifying the upper range extreme based on the sub-set's conditions.

Table 2. Ranges of Sobol values assumed in the parametric analysis. Before developing the parametric analysis, the upper and lower limits of each range were updated based on the considered sub-set.

Input parameter	Range of admissible values	Unit measure	Source used to define the range of values
N	integers between 5 and 100	-	(Cantini et al., 2022)
SL	floats between 0.85 and 0.99	-	(Cantini et al., 2022)
$\overline{D}_{1c_k}$	integers between 1 and 7	units/year	(Knofius et al., 2021)
$t\ central$	floats between 100 and 2,000	€/transportation	(Cantini et al., 2022)
c_{b_k}	floats between 1,000 and 100,000	€/backorder	(Peron et al., 2021)
L_k	integers between 4 and 26	weeks	(Knofius et al., 2021)
K	integers between 10 and 5,000	-	Authors' choice
n_k	floats between 1 and 3	-	(Knofius et al., 2021)
uc_k	floats between 10 and 2,500	€/unit	(Knofius et al., 2021)

4.3. Step iii – DSS development

Finally, in Step iii, the results of the parametric analysis were used to feed and train a decision tree algorithm (using Python's Sklearn library). Therefore, the DSS was achieved (one per each sub-set), providing spare parts retailers with a guide to review the design of existing SCs in a multi-item perspective. A decision tree algorithm was selected to develop the DSS, being renowned as a quick and user-friendly machine learning algorithm, which allows understanding and interpreting the correlations among many parameters affecting a system (Arena et al., 2021).

Specifically, in the training process, the Sobol values assumed by the following parameters (in each of the 1,000,000 scenarios) were given as input attributes to feed and train the DSS: N, SL, $\overline{\overline{D_{1c}}}$, $t\ central$, $\overline{c_b}$, $\overline{L}$, K, $\overline{n}$, and $\overline{uc}$. Moreover, the identifier of the optimal SC design ($i = 0 - 10$ in Figure 4) associated with each scenario through the heuristic model was indicated as target label that the decision tree algorithm should learn to forecast. Finally, the Gini diversity index (gdi) was used at each node of the tree to split the starting data points into binary groups (branches) with the maximum purity, according to Equations 51-52.

$$gdi = 1 - \sum_{x=1}^{X} p(x)^2 \tag{51}$$

$$min\left(\frac{n_{left}}{n} gdi_{left} + \frac{n_{right}}{n} gdi_{right}\right) \tag{52}$$

Where, as reported by Arena et al. (2021), X is the total number of target labels to be assigned (eleven SC designs in Figure 4), $p(x)$ is the probability of picking a data point with the target label x, n is the number of data points in the original node, n_{left} is the number of data points falling into the new node on the left branch, n_{right} is the number of data points falling into the new node on the right branch, gdi_{left} is the Gini diversity index of the new node on the left branch, gdi_{right} is the Gini diversity index of the new node on the right branch, and the final nodes of the tree (achieved after the last split of each branch) are called leaves.

To validate the performance of the tree and avoid under- or over-fitting issues, a k-fold cross-validation process (with five folds) was carried out together with a cost-complexity pruning of the tree. The cost-complexity pruning was useful not only to avoid over-fitting (Morgan et al., 2003), but also to generate a user-friendly DSS. Indeed, as described by Bradford et al. (1998), by imposing a specific cost-complexity parameter (α), the leaves characterised by the weakest links according to Equation 53 were recursively removed, promoting the healthy growth of the tree by containing its size and complexity (the pruned leaves were collapsed into the node which was hierarchically superior to them within the same branch).

$$R_\alpha(T) = R(T) + \alpha|T| \tag{53}$$

In Equation 53, $R_\alpha(T)$ is the cost complexity measure of the tree (T), $|T|$ is the number of leaves of the tree, and $R(T)$ is given by the sum of misclassification errors made at each leaf of the tree.

To prune the tree, the value of α was selected after accomplishing a sensitivity analysis as follows. Several decision trees were developed by imposing different α values. Hence, their total accuracy (A, Equation 54) was calculated as the ratio between the number of correct forecasts made by the tree ($\#correct\ forecasts_{tree}$) and the total number of forecasts ($\#forecasts_{tree}$, that is the number of starting data points). Based on the achieved results, α was chosen as the value which produces a trade-off decision tree characterised by a high accuracy and a reduced size (which results in DSS user-friendliness).

$$\boldsymbol{A} = \frac{\#correct\ forecasts_{tree}}{\#forecasts_{tree}} \tag{54}$$

Finally, the selected trade-off tree was taken as the DSS of this study (one per each sub-set), and its performance was evaluated not only by defining the tree accuracy (A), but also determining other three Key Performance Indicators (KPIs), as suggested by Cantini et al. (2022):

- The accuracy of each leaf (a, Equation 55), calculated as the ratio between the number of correct forecasts ($\#correct\ forecasts_{leaf}$) and the number of total forecast in the leaf ($\#forecasts_{leaf}$).

$$a = \frac{\#correct\ forecasts_{leaf}}{\#forecasts_{leaf}} \tag{55}$$

- The number of elements in each leaf (p, Equation 56), calculated as the ratio between the number of elements classified within the considered leaf (($\#forecasts_{leaf}$) and the number of total elements to be classified ($\#forecasts_{tree}$, that is the number of starting data points).

$$p = \frac{\#forecasts_{leaf}}{\#forecasts_{tree}} \tag{56}$$

- The expected percentage of cost increase (c, Equation 57) to be paid by spare part retailers in case an element is wrongly classified in a leaf, calculated as the average of cost increases associated with wrong tree forecasts.

$$c = \frac{\sum_{h=1}^{\#wrong\ forecasts_{leaf}}\left(\left|\frac{cost\ of\ wrong\ forecast - cost\ of\ correct\ forecast_h}{cost\ of\ correct\ forecast_h}\right| * 100\right)}{\#wrong\ forecasts_{leaf}} \tag{57}$$

5. Results and discussion

This Section shows the results of the methodological framework, discussing the achieved DSSs.

Considering spare parts retailers who have optimised stock deployment policies of CM spare parts, then dividing SKUs into the sub-sets of Figure A.1, we applied the methodological framework to each sub-set, thus achieving three DSSs. In this Section, we present the DSS related to sub-set with $Deg_{CM} = 0$ (blue in Figure A.1), while reporting the other two DSSs in Appendix B.

Concerning the sub-set with $Deg_{CM} = 0$, aiming to obtain a DSS that is both accurate and user-friendly (namely, easy-to-read), we carried out the sensitivity analysis of Figure 6, investigating the decision tree accuracy (A) related to different cost-complexity parameters (α). Based on the results of Figure 6, we determined how to prune the tree, taking as DSS the decision tree with $\alpha = 0.015$ (red dot), which is considered a trade-off between user-friendliness and accuracy. Figure 7 shows the achieved DSS, which suggests the optimal SC design (0-10 in Figure 4) with a total accuracy of $A = 86.5\%$.

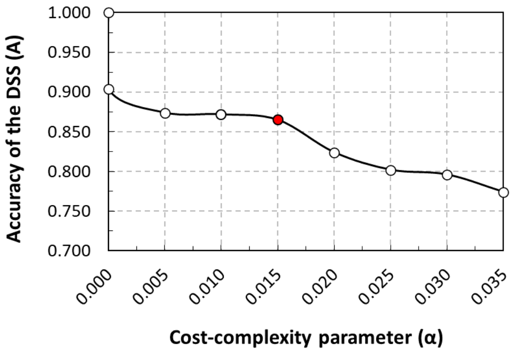

Figure 6. Sensitivity analysis on DSS's accuracy.

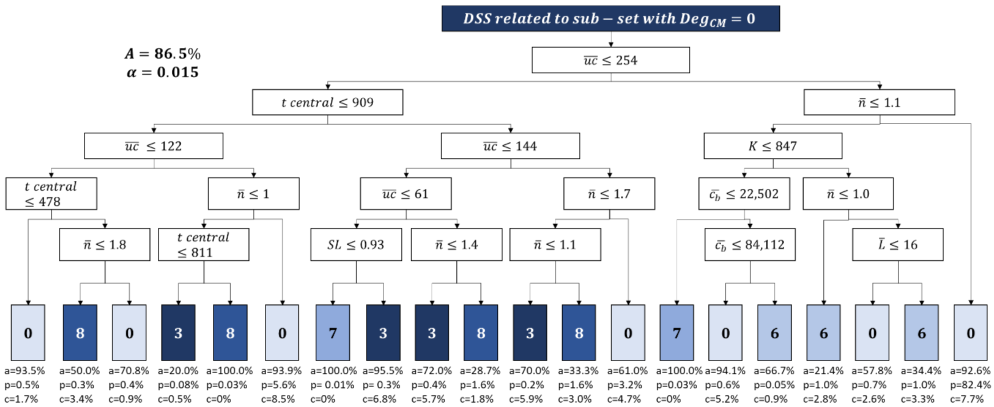

Figure 7. DSS related to sub-set with $Deg_{CM} = 0$*.The numbers inside the leaves refer to Figure 4.*

The decision levels of the DSS (associated with branch splits) are defined based on the relative importance of input parameters on the selection of the optimal SC design. The relative importance is calculated by summing the changes in the Gini Diversity Index (weighted by the node probability due to splits at each parameter), and then dividing the sum by the number of branch nodes (Lolli et al., 2022). Based on this, Figure 7 proves that, among the input parameters of the DSS (related to sub-set with $Deg_{CM} = 0$), N and $\overline{D_{1c}}$ have a low impact on the process of selecting the optimal SC design. Indeed, they do not appear in the final DSS (low relative importance). Conversely, $\overline{uc}$, $\bar{L}$, $t\ central$, K, $\bar{n}$, SL, and $\bar{c_b}$ affect the DSS, especially $\overline{uc}$, $t\ central$, and $\bar{n}$, which appear in the first decision levels of the tree (high relative importance), also guiding most of branch splits. Moreover, Figure 7 shows that, among the optimal SC designs, that with identifier 0 (Figure 4) is the most frequently suggested, appearing in 35% of the leaves, and influencing 93.4% of the DSS's forecasts (p sum). This result proves that, regarding the sub-set characterised by $Deg_{CM} = 0$, keeping the starting SC design unchanged is often convenient, avoiding investing in AM. Besides SC design $i = 0$, those with identifiers 3 and 8 are also repeatedly suggested, appearing in 20% of the leaves, and representing, respectively, 0.98% and 3.53% of the DSS's forecasts. Therefore, in some cases, the DSS suggests a single-sourced SC design where all SKUs are produced in-house as AM spare parts and a hybrid deployment policy is adopted ($Deg_{AM} = 0.50$). Moreover, in other cases a dual-sourced SC is recommended where CM SKUs are managed with $Deg_{CM} = 0$ and AM SKUs are managed with $Deg_{AM} = 0.50$. Conversely, Figure 7 shows that inventory centralisation is not cost-effective, since SC designs with $Deg_{AM} = 0.75$ and 1 are never suggested (4-5 and 9-10, Figure 4). Finally, the KPIs a, p, and c in Figure 7, allow spare parts retailers to accept the DSS results, ensuring that its forecasts lead to leaves characterised by high accuracy ($a > 90\%$) or, at least, low percentage of cost increase ($c < 10\%$). This means that the DSS predictions are accurate or, in case they are wrong, they imply a negligible increase in costs that spare parts retailers should pay compared to that of the optimal SC design. It is worth mentioning that the above comments relate to Figure 7. However, similar considerations can be derived from DSSs linked to other sub-sets (Appendix B).

In conclusion, spare parts retailers can leverage DSSs' results by consulting Figure 7 and Figures B.1-B.2 according to the logic summarised in Figure 8, where three alternatives arise.

- If the DSS suggests continuing purchasing all SKUs as CM spare parts (0 in Figure 4), spare parts retailers should keep the starting SC design unchanged and there is no need to apply the heuristic model of Step i (more accurate than the DSS, but onerous in terms of time consumption and resource computations) to get specific information on individual SKUs.
- If the DSS suggests producing all SKUs with AM ($1-5$ in Figure 4), again there is no need to apply the heuristic model. In fact, all SKUs should be produced with AM and the number of 3D printers to be installed in each DC can be determined via Equations 42 and 48;
- Finally, if the DSS suggests producing some SKUs through AM, while purchasing the others as CM (dual-sourced SC, 6-10 in Figure 4), in this case, it is worth applying the heuristic model to deepen the specific SKUs to be produced with AM and the optimal number of 3D printers to be installed in DCs.

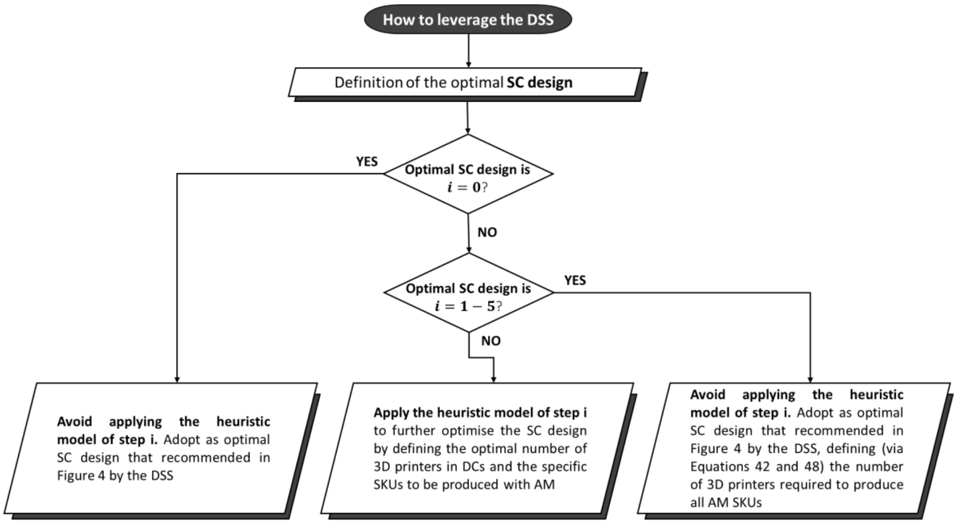

Figure 8. Guidelines to leverage the DSSs.

5.1. DSS application on a case study

The DSS related to sub-set with $Deg_{CM} = 0$ (Figure 7) was applied to a case study company, aiming to show with an example how the findings of this work can be used, also testing the considered DSS. The case study company distributes aircraft spare parts to twenty main customers (N) and its existing SC includes four DCs. Within each DC, spare parts are stocked according to a (ROP, Q) supply policy, where CM SKUs are purchased by a supplier, who serves all DCs. Eight SKUs (K) are managed by the company, which are aircraft components distributed with a service level of 95%. The average procurement lead time is equal to 8 weeks (L_k) for all SKUs (being defined by contracts with the supplier). The average demand of SKUs and their unitary cost are reported in Table 3. The unitary transportation cost from a DC to a customer was estimated to be $t\ central = 550\ €/transportation$ (based on the vehicles used and the average distance between DCs and customers). Finally, according to company assessments, the unitary backorder cost of all SKUs was estimated to be around $c_{b_k} = 20{,}000\ €/backorder$. Indeed, these SKUs are critical for the functioning of aircrafts, and their stock-outs cause problems of vehicle unavailability for customers. The company was interested in evaluating if this starting SC design (with $Deg_{CM} = 0$) was optimised or should be reviewed. Moreover, they wanted to evaluate the economic convenience of producing in-house AM spare parts instead of buying CM stocks.

Table 3. SKUs managed by the case study company.

SKU	$\overline{D}_{1c_k}$ [units/year]	uc_k [€/unit]
A	6	3,500
B	8	650
C	6	10,300

D	6	17,690
E	23	150
F	12	525
G	7	500
H	9	340

The company had already optimised the stock deployment policies of CM spare parts following Cantini et al. (2022) and adopting $Deg_{CM} = 0$ for all SKUs. This choice can be confirmed by consulting Figure A.1, where all SKUs fall under sub-set with $Deg_{CM} = 0$. Focusing on this sub-set, the DSS in Figure 7 was consulted to review the SC design. To do so, the average cost of SKUs was calculated ($\overline{uc} = 4{,}207$ €$/unit$), and the average production cost of each AM SKUs was estimated to be on average less expensive than the purchasing cost of the equivalent CM spare parts ($\bar{n} = 0.9$). Based on this, Figure 7 suggested as optimal SC design the one characterised by identifier $i = 7$ (dual-sourced SC, where $Deg_{CM} = 0$ and $Deg_{AM} = 0.25$). Since the suggested SC design involved dual-sourcing, according to Figure 8 the heuristic model was applied to the specific case study, aiming to obtain detailed information on individual SKUs. The heuristic model validated the results of the DSS, suggesting as optimal the SC design $i = 7$. Finally, the heuristic model allowed to determine which SKUs to produce with AM (A, C, D, G, H) and which to purchase as CM finished products CM (B, E, F), also suggesting installing in each DC one 3D printer.

6. Conclusions

This paper supports spare parts retailers in reviewing the design of existing SCs, selecting, for each SKU, the optimal manufacturing technology (AM or CM) and the optimal stock deployment policy (centralised, decentralised, or three hybrid stock deployment policies). As the starting condition, spare parts retailers who purchase CM spare parts from suppliers and distribute them to customers are considered. Moreover, spare parts retailers are supposed to have already optimised stock deployment policies of CM spare parts, adopting methodologies such as that by Cantini et al. (2022), then splitting SKUs into sub-sets. On top of this, in this paper, a DSS is provided per each sub-set to help spare part retailers in selecting the most cost-effective SC design among eleven ones, which are distinguished by varying the stock deployment policies (investigating the five aforementioned alternatives) and considering: (i) single-sourced SCs where all SKU are CM spare parts purchased from suppliers; (ii) single-sourced SCs where all SKUs are AM spare parts produced in-house; (iii) dual-sourced SCs where some SKUs are produced as AM spare parts, while the others are purchased as CM.

To develop the DSS, a decision tree algorithm was chosen, being renowned as a quick, and user-friendly tool, which allows the robustness of decisions to be measured with proper KPIs. Moreover, it exploits the capability of machine learning to understand and interpret correlations among many parameters affecting a system. To achieve the DSS, a three-steps methodological framework was followed for each sub-set, where: in Step i, a heuristic model was developed (based on a preliminary initialisation and three nested iterative loops) to compare the total costs of eleven SC designs. In Step ii, a parametric analysis was performed, collecting a sample of 1,000,000 realistic SC scenarios, and submitting each of them to the heuristic model (determining its optimal SC design). Finally, in Step iii, the parametric analysis was used to feed and train a decision tree, which was pruned based on a sensitivity analysis to achieve a DSS representing a trade-off between user-friendliness and accuracy of predictions.

The developed DSSs (one per each sub-set) represent the main contribution of this study, since nothing similar has been done before. In fact, it is well known that an efficient SC design improves the performance of a spare part retailer, minimising SC costs and guaranteeing high service levels. However, to the best of our knowledge, the only DSS provided by the literature to support spare parts retailers in reviewing the SC design (quantitatively capturing the differences between SCs with CM and AM spare parts) does not investigate the in-house production of AM spare parts, also neglecting fixed costs of 3D printers and the optimisation of SC designs with multiple SKUs at the same time. Based on this, at a theoretical level, this study fills the aforementioned literature gap, providing DSSs and a heuristic model capable of suggesting under which conditions it is economically advantageous to have centralised, decentralised, or hybrid stock deployment policies, also selecting the optimal spare parts manufacturing technology (comparing the CM purchase with the AM in-house production, and considering fixed costs of 3D printers and the optimisation of multiple SKUs at the same time). At a practical level, this study provides spare parts retailers with a quick and user-friendly DSS for determining how to review the design of existing SCs. Therefore, the provided DSS could help spare parts retailers in remaining competitive on the market, maintaining an alignment between logistic activities and customer needs despite spare parts demand fluctuations.

The main findings of this study can be summarised as follows: the DSS provided for each sub-set is robust since a decision tree with accurate leaves is achieved or, at least, the DSS forecasts prevent spare parts retailers from paying a high percentage of cost increase (always less than 10%, often below 5%) in case of wrong predictions. Moreover, the DSS related to each sub-set proves that, despite the advantages of risk-pooling, centralisation of spare parts (in SCs with Deg_{CM} or Deg_{AM} higher than 0.75) is rarely advantageous, being never suggested as cost-effective. Conversely, decentralised and hybrid SCs are often convenient, especially with Deg_{CM} or $Deg_{AM} \leq 0.25$ (which cover 79.2% of the leaves of Figure 7 and Figures A1-A2). Finally, input parameter N has a low impact in the decision-making process, not appearing in Figure 7 nor in Figures A.1-A.2. After building a DSS per each sub-set, one of them was tested on the case study of an aircraft spare parts retailer to validate its results and, above all, to show with an example how to leverage the findings of this work. The results showed how to consult the DSS, proving how quickly spare parts retailers can compare their current SC design with the optimal one (only four questions were answered in Figure 7 before defining the optimal SC design).

Future developments of this study could be twofold. First, to evaluate the possibility of producing AM spare parts on-demand. Indeed, AM production times are, currently, too slow to compete with CM production in an on-demand policy. However, in the future, AM technology will advance, and an on-demand AM production could become cost-effective and worth to be investigated. Second, to relax some assumptions underlying this study, which were made to achieve a quick and user-friendly DSS, suitable for taking strategic decisions on the SC design. For instance, next studies could remove the need for splitting SKUs into sub-sets, also investigating stochastic procurement lead times, SC sustainability problems, and the transportation of multiple spare parts at the same time.

Appendix A

As the starting condition for this study, we consider spare parts retailers who manage CM spare parts, having optimised their stock deployment policies, and having divided SKUs into sub-sets. Since not all spare parts retailers may have already optimised their stock deployment policies, in this study we facilitated the accomplishment of this task as follows. We applied the methodology by Cantini et al. (2022) focusing on CM spare parts (excluding AM variables). Therefore, following the authors' instructions, we derived Figure A.1, which guides spare parts retailers in identifying the conditions (combinations of the input parameters of Table 1) under which individual CM SKUs (k) should be associated with different sub-sets. Figure A.1 shows that Cantini et al. (2022) suggest splitting CM SKUs in only three sub-sets (characterised by Deg_{CM} equal to 0.50, 0.25, and 0, respectively), while underlining as not cost-effective for CM spare parts the other stock deployment policies (Deg_{CM} equal to 0.75 and 1, Figure 1).

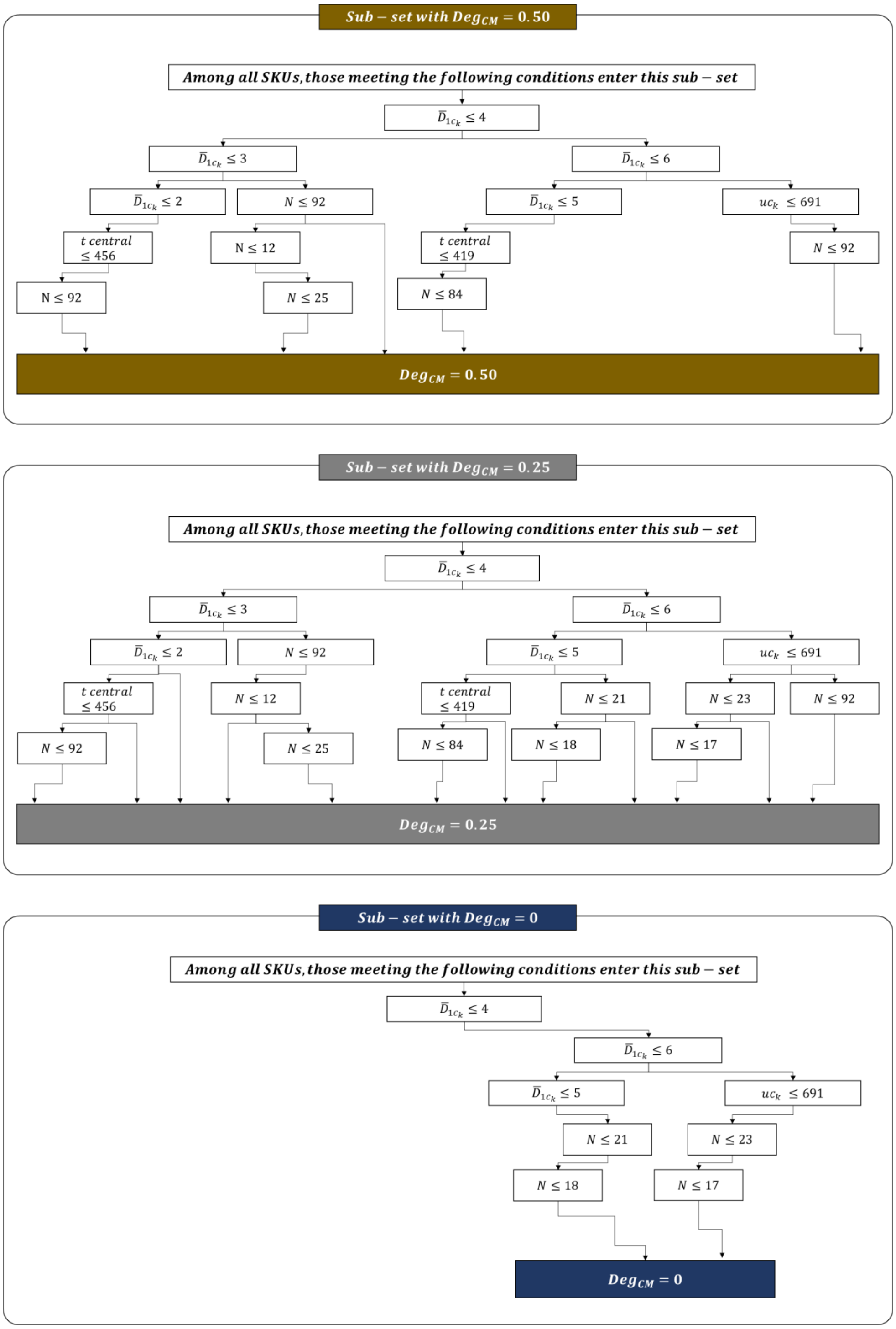

Figure A.1. Conditions suggested by Cantini et al. (2022) to divide CM SKUs into three sub-sets, according to their optimal stock deployment policy (Deg_{CM}).

Appendix B

Considering spare parts retailers who have already divided SKUs into the sub-sets of Figure A.1, we applied the methodological framework to each sub-set, achieving three DSSs. The DSS related to sub-set with $Deg_{CM} = 0$ (Figure A.1) was presented in Section 5, while the other two DSSs are reported below. Particularly, Figure B.1 shows the DSS related to sub-set with $Deg_{CM} = 0.25$, while Figure B.2 depicts the DSS related to sub-set with $Deg_{CM} = 0.50$.

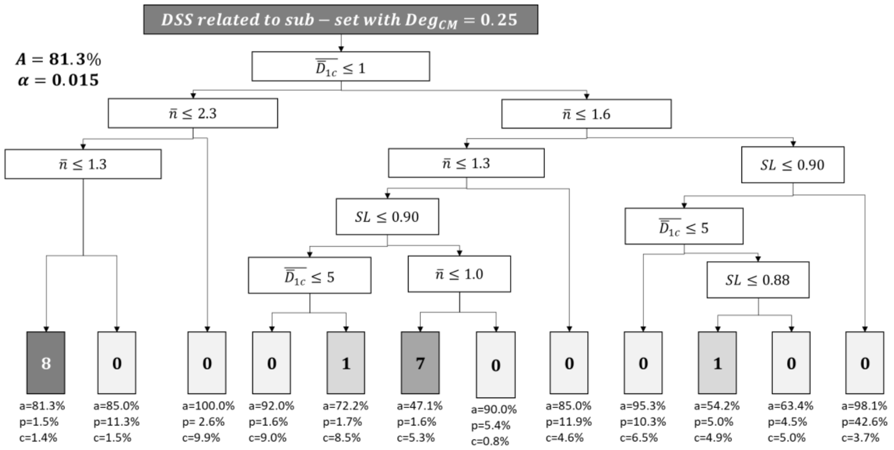

Figure B.1. DSS related to sub-set with Deg_{CM} = 0.25.

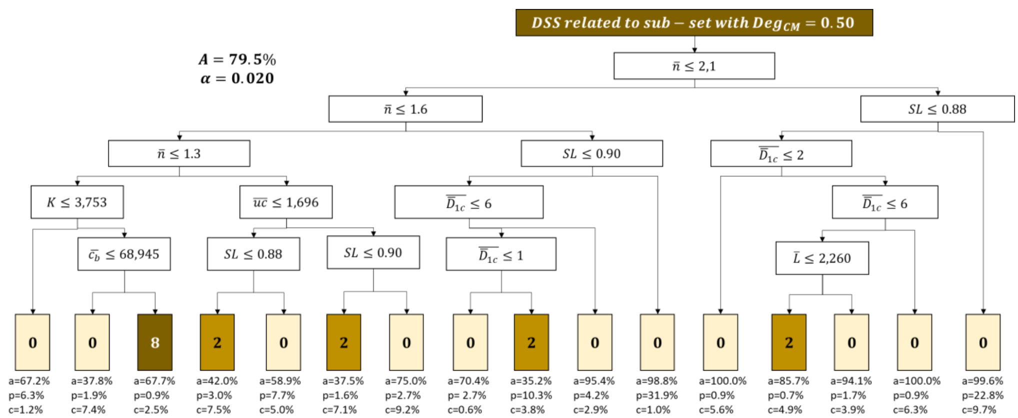

Figure B.2. DSS related to sub-set with Deg_{CM} = 0.50.

Data availability statement

The authors confirm that the data supporting the findings of this study are available within the article [and/or] its supplementary material.

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