Spare parts classification and demand forecasting for stock control: Investigating the gap between research and practice

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Abstract

This paper investigates the gap between research and practice in spare parts management, with specific reference to durable goods addressed to private or professional customers. The paper provides a critical literature review of theoretical contributions about spare parts classification and demand forecasting for stock control. The discussion of ten case studies, then, allows to analyze the reasons for this gap, by addressing the limitations of models developed in literature, the role of contextual factors and the maturity in companies' spare parts management practices. Four main directions for research are proposed in order to bridge the gap, namely: to develop integrated approaches to spare parts management; to define contingency-based managerial guidelines, to favor the knowledge accumulation process in companies, and to supplement theoretical models with practical relevance.

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1. Introduction

Service parts for products like household appliances, automobiles and copy machines has grown into a business worth more than a $200 billion worldwide [1]. Spare parts inventories need to be available at appropriate points within the supply chain, to provide after-sales services and to guarantee the desired service level [2]. However, several aspects concur in making demand and inventory management for spare parts a complex matter: the high number of parts managed [3]; the presence of intermittent or lumpy demand patterns [4]; the high responsiveness required due to downtime cost for by customers [5]; and the risk of stock obsolescence [3].

Research on spare parts demand and inventory management developed specific methods in the last decades, such as the application of Croston's method [6] and its successive modifications [7] to spare parts demand forecasting. On the other hand, in recent years, companies increased investments in spare parts management: Aberdeen Research estimated the total market size for service parts management software at over $100 millions in 2005 [8]. Despite that, after-sales service and spare parts management in several companies manufacturing and selling durable consumer products has been traditionally overlooked [9], and the management techniques adopted are often not differentiated from the ones used for finished products or components used in production [10]. As pointed out by Boone et al. [11] and Aberdeen Group [12], moreover, managers lament the lack a system perspective in spare parts management, the weakness of supply chain relationships, the inaccuracy of demand forecasts, and the difficulty in maintaining an effective level of parts inventory turns. In addition, the frequency of product innovation requires to manage demand and inventory also for parts for which historical demand or failure data are not available [11].

Such problems encountered in business practice suggest the existence of a research–practice gap [3,16]. Although the issue of a research–practice gap has been discussed in production, inventory and demand management (e.g. [13–15]), very scarce empirical research has addressed the field of spare parts management.

The objective of this paper is, therefore, to investigate the existence and the reasons for such a gap between research and practice in spare parts management. Firstly, the paper aims to provide a critical literature review of research, focusing in particular on spare parts classification, demand forecasting, and their integration with spare parts inventory control. Secondly, through the findings from ten case studies of companies manufacturing durable goods addressed to private or professional customers, we aim at analyzing the reasons for this gap. Third, the conceptual tools used for the analysis (the contingency perspective and a knowledge maturity model) and the discussion in the light of the literature, allow to identify four directions for future research in order to bridge the aforementioned gap.

The remaining of the paper is organized as follows. Section 2 provides a literature review of studies addressing spare parts classification, demand forecasting, their integration with inventory management and the gap between research and practice in spare parts management. Section 3 describes the methodology...
adopted for the empirical research. Section 4 presents the findings from ten case studies, comparing the spare parts management practices of the analyzed companies. In Section 5, the findings are discussed in the light of extant literature, Section 6 identifies directions to reconcile research and practice, while the final section points out some conclusive remarks and the limitations of this study.

2. Background

This section proposes a critical review of literature about spare parts management. For spare parts classification (Section 2.1) and demand forecasting methods (Section 2.2) we undertook a comprehensive literature review in main journals dealing with operations management, forecasting and operations research, identifying, respectively, 25 and 29 references (one appears in both sections).\(^1\) We also analyze how these papers relate these aspects with stock control (in Section 2.3). In the vast area of spare parts inventory management modeling, instead, readers may resort to previous literature reviews, such as [17]. Finally, seven papers discussed in Section 2.4 deal with the gap between research and practice for spare parts management.

2.1. Spare parts classification

As pointed out by Boylan and Syntetos [10], spare parts for consumer products are highly varied, with different costs, service requirements and demand patterns. A classification of spare parts, therefore, is helpful to determine service requirements for different spare parts classes, and for forecasting and stock control decisions.

Table 1 summarizes the literature on classification methods for spare parts. In the review are also included works referring more generally to low demand items, and some of the most-known general approaches to item classification. In total we analyzed 25 papers, 18 of which have proposed classifications developed for, or applied to, spare parts. The others, [18–24], dealt instead (also) with slow moving demand items.

Most of the analyzed papers propose multi-criteria classification methods, which take into account various factors. Only four papers [25,18,26,27] propose mono-criterion methods. It is also important to notice that some papers propose the classification criteria as their main contribution (e.g. [18,28,26]); for some others, instead, classification criteria are defined only within examples of application of a proposed classification methodology (e.g. [21,23,22,24,29]).

Table 1 groups criteria into categories. The most popular criteria, both appearing in 15 works, relate to part cost (unit or inventory cost), and part criticality. Other popular types of criteria are: demand volume or value (appearing in 13 contributions), supply characteristics, such as replenishment lead time, supplier availability and risk of non-supply (indicated by 12 studies), and demand variability, reported in 8 contributions—three of which include the measure of lead time variability [30–32]. Other criteria, proposed by fewer studies concern the part life cycle phase [33–35], specificity [36,37], and reliability [33].

Although several criteria have been proposed, very little attention has been dedicated to identifying in which context a criterion is preferable to others. Only Boylan and Syntetos [10] suggests that part criticality is more appropriate for technical systems rather than products used by private customers.

Table 1 also categorizes the literature according to the classification technique proposed (i.e. in which way parts are classified once the criteria have been defined). Most papers adopt quantitative classification techniques. The most common is the ABC approach, proposed in 10 contributions. It is used for a single criterion, generally demand volume [25,27], and for multi-criteria classifications. Different methods are proposed to implement multi-criteria ABC classifications: matrix models [38,19], weighted linear optimization [21–23], artificial neural networks [20], weighted Euclidean distances with quadratic optimization [24], and the fuzzy logic [29]. A part from ABC, different quantitative classification techniques are developed. A demand-based classification is proposed by Syntetos and Boylan [31] and Boylan et al. [32], through a two-dimensional matrix based on demand variability (cv\(^2\)) and order frequency, while Williams [18] and Eaves and Kingsman [30] propose the partitioning of demand variance during the lead time. Yamashina [33] proposes the definition of product-still-in-use quantity curves and service part demand curves as inputs for spare parts classification. Nagarur et al. [39] and Porras and Dekker [40], instead, propose a hierarchical two- or three-dimensional quasi-quantitative classification. Ernst and Cohen [28] apply the Operation Related Groups methodology, based on a clustering technique, on 40 different variables, and finally Petrovic et al. [41] and Petrovic and Petrovic [42] propose an expert system combining the determination of failure rates and fuzzy logic.

On the other hand, qualitative methods try to assess the importance of keeping spare parts in stock based on information on the specific usages of spares and on factors influencing their management (costs, downtime, storage considerations, etc.). The Vital, Essential, Desirable (VED) is a qualitative method based on consultation with experts [43]. Despite its apparent simplicity, structuring a VED analysis might be a difficult task, as its accomplishment may suffer from the subjective judgements of users [37]. In order to limit this problem, VED may be combined with a systematic procedure for classifying spare parts. For example, Gajpal et al. [26] propose a VED classification model based on the use of the Analytic Hierarchic Process (AHP) procedure [44,45], defining three groups of spare parts (vital, essential and desirable). A similar approach is proposed by Sharaf and Helmy [34], who consider five criteria and four alternative modes for each criterion, determining four groups of spare parts: vital, essential, important, desirable. More complex is the approach adopted by Braglia et al. [46], in which the decision tree about the multiple attributes analyzed (e.g. inventory constraints, lost production, logistic aspects) is integrated with a set of AHP models, in order to solve the various multi-attribute decision sub-problems at the different nodes of the decision tree. Finally, Huisken et al. [36] and Cavalieri et al. [37] do not propose a specific technique for classifying spare parts according to the proposed criteria.

Table 1 also reports about the empirical applications of the proposed criteria and techniques. Only seven works [25,37,30,32,40,35,27] report classification methods that have been actually implemented by companies. Some other papers report a case study as well, but just as a test of the proposed methodology [18,19,28,26,34,20,46,37,24,29], while some others [31,21,22,23,36] present only a simulated quantitative or qualitative application on real or hypothetical data. Four works [38,33,41,42], finally, do not report any application case. Eventually, aspects and obstacles related to the practical applicability of the classification methods, such as data availability, implementation algorithms, classification update,
Table 1
Overview of the main spare parts classification contributes.

<table>
<thead>
<tr>
<th>Reference number</th>
<th>Mono criteria</th>
<th>Multi-criteria</th>
<th>Classification technique:</th>
<th>Application case</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Part cost/value</td>
<td>Part criticality</td>
<td>Supply characteristics/uncertainty</td>
<td>Demand volume/value</td>
</tr>
<tr>
<td>[25]</td>
<td>X</td>
<td>X</td>
<td></td>
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<tr>
<td>[18]</td>
<td>X</td>
<td>X</td>
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<td>[38]</td>
<td>X</td>
<td>X</td>
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<td>[33]</td>
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<td>[28]</td>
<td>X</td>
<td>X</td>
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<td>[42]</td>
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<td>[46]</td>
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<td>[30]</td>
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<td>[32]</td>
<td>X</td>
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<tr>
<td>[24]</td>
<td>X</td>
<td>X</td>
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<tr>
<td>[29]</td>
<td>X</td>
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<td>[40]</td>
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<td>[27]</td>
<td>X</td>
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<tr>
<td>[35]</td>
<td>X</td>
<td>X</td>
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</tbody>
</table>
solution sensitivity to thresholds or the role of judgment, are discussed only by Huiskonen [36], Boylan et al. [32], and Syntetos et al. [27].

In summary, following Syntetos et al. [27], we believe that the issue of classification has not received as much academic attention as its implications on spare parts management would require, although it has increased in the last decade, when 16 of the 25 analyzed papers were published. In particular, there is a strong need for case studies describing real implementation of classification methods and focused on their practical applicability problems.

2.2. Spare parts demand forecasting

Fast moving parts may not require ad hoc forecasting methods, but a large portion of spare parts are characterized by intermittent or lumpy demand [10], requesting special attention. Moreover, demand for spares may be related to some explanatory variables (e.g. failure occurrence, maintenance activities). Despite the importance of demand forecasting for stock control, however, spare parts research has mostly focused on inventory modeling [47]. Only recently demand forecasting for spare parts (or more generally for lumpy demand items) has been the object of renewed research attention, and only one study to date carries out a review of spare parts forecasting literature [4]. It provides a useful framework to classify contributions according to the three phases of forecasting: pre-processing (i.e. rules that designate a spare part as slow or fast-moving, intermittent or lumpy); processing (the application of the appropriate forecasting method) and post-processing (adjustments made by the forecast user). This section provides an extension of the review in [4], focusing on the processing phase (most of the papers classified in Section 2.1 belong, instead, to the pre-processing phase). Given the relatively little specific attention devoted to spare parts, also some relevant work on intermittent demand forecasting is considered. A summary of the reviewed works is reported in Table 2, which groups literature according to the kind of method developed. Table 2 lists 28 contributions, 16 of which are from the last decade. If we refer only to papers specifically addressing spare parts, or applying methods to spare parts demand forecasting, we find out 13 works, 12 of which are from the years 2000s.

Time series demand forecasting methods have been applied to spare parts. Traditional time-series methods, such as moving average [48] or single exponential smoothing [49,50] are still the most used in business practice. However, they have been shown to overestimate the mean level of intermittent demand, if applied immediately after a demand occurrence [4]. Johnston and Boylan [51] proposed an adjusted exponentially weighted moving average method (EWMA method) for forecasting intermittent demand. They show that it performs better (in terms of mean square of the forecast errors) than a traditional EMWA for an inter-order interval higher than 1.25 forecasting periods.

Altay et al. [52] and Bermudez et al. [53], instead, developed modifications to the Holt and Holt–Winters methods, respectively, for intermittent demand in presence of trend or trend and seasonality. In particular, Altay et al. [52] apply a modification of Holt’s double exponential smoothing method developed by Wright [54] to forecast intermittent demand with trend, both in a simulated environment and with a real data set of aircraft parts demand. Metrics on inventory levels and service implications show that their method presents higher service levels but also higher inventories than other specific forecasting methods (in particular the one by Syntetos and Boylan [7], described later), with no significant difference in the total cost.

A seminal work in the field of intermittent demand forecasting is the one by Croston [6]: he suggested a method forecasting separately, through single exponential smoothing, the interval between demand arrivals and the demand size (see also [55,56]). Syntetos and Boylan [57] showed that Croston’s estimator is biased and proposed an adjusted method, showing its superior performance [7]. Leven and Segerstedt [58] use the Croston approach of only updating when there is a positive demand, but update the forecast for the demand per period directly using the ratio of demand size and interval. Their method, nonetheless, was demonstrated being biased as well [59].

Bootstrapping was also applied to forecasting intermittent demand [60,61]. Bootstrapping methods do not require to make an assumption on the distribution of demand. The method by Willemain et al. [61] modifies the traditional bootstrapping approach [62] in order to take into account autocorrelation, frequent repeated values and relatively short series, aspects often occurring in spare parts demand. Using nine industrial datasets,

Table 2

<table>
<thead>
<tr>
<th>Class</th>
<th>Forecasting method</th>
<th>Reference number</th>
<th>Classification</th>
<th>Application to spare parts forecasting</th>
</tr>
</thead>
<tbody>
<tr>
<td>Traditional time series</td>
<td>Traditional time series: moving average, exponential smoothing, EWMA</td>
<td>[49,50,48]</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Modified traditional time series</td>
<td>Adjusted EWMA</td>
<td>[51]</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Croston's method and modifications</td>
<td>Croston</td>
<td>[53,52]</td>
<td>X</td>
<td>X [47]</td>
</tr>
<tr>
<td>Bootstrapping</td>
<td>Croston modified</td>
<td>[60,61]</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Demand aggregation/disaggregation</td>
<td>Order Overplanning</td>
<td>[64,65]</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Analysis of reliability</td>
<td>Failure rate analysis</td>
<td>[33,76]</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Regression</td>
<td>Integrated Forecasting Method</td>
<td>[74]</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Neural networks</td>
<td>Neural networks</td>
<td>[71]</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Bayesian approach</td>
<td>Beta-binomial model (allowing for different demand variance)</td>
<td>[77]</td>
<td>X</td>
<td>X</td>
</tr>
</tbody>
</table>
they compare their method with Croston’s and exponential smoothing, achieving a higher forecasting accuracy. Although their results received some criticism [63], bootstrapping represents an interesting alternative to Croston’s and its variants, especially in cases in which short data history limit the reliability of time series methods.

Other works focus on filtering demand data: Kalchschmidt et al. [64,65] propose disaggregate time series, in order to separate a stable demand series from an irregular (and lumpy) one. To the different demand series thus generated, different forecasting methods could be applied. In the spare parts case discussed in [64] the authors apply a single exponential smoothing to the stable demand series and a modified Croston’s procedure to the lumpy one, obtaining reduced inventory levels, for given service level objectives. A contribution of [64] stands in the consideration of the supply chain structure and the customers’ characteristics as determinants of demand patterns and therefore of the forecasting method to be adopted. The case study considers, moreover, a quite common situation in durable consumer goods, in which the product manufacturer provides spare parts to a large network of small customers (e.g., repair shops) and a smaller amount of large customers, such as regional warehouses, subsidiaries and wholesalers.

Kalchschmidt et al. [64] also treat the value of advance demand information from customers. This issue is modeled in lumpy contexts by Verganti [66] through the order overplanning model, which considers early information collected from customers as a driver for demand forecasts. Another method exploiting early information is Early Sales [67,68]: in this case, orders from customers with longer lead times are used to make a forecast of the remaining demand. The application of this method to lumpy demand is provided in [69]. These two methods, however, seem ill-suited for forecasting spare parts requirements in durable consumer goods industries. Order overplanning, in fact, requires a knowledge and the collection of advanced information from a large amount of customers in order to define the probability of receiving orders. This seems unlikely in contexts with numerous customers and items, and in which demand may be triggered by unexpected events (product failures). On the other hand, the Early Sales method requires a portion of customers to place orders in advance, and those requests from early buyers to be correlated with the other customers. These hypotheses may not be suited for spare parts, where deliveries are generally requested urgently, and the demand correlation among customers cannot be given for granted, given the nature of events triggering demand. Nevertheless, improving forecasts and/or logistic performance through buyer–supplier information exchange is a relevant issue also for spare parts. [4] acknowledge a potential for savings related to information sharing, but highlight the need for more research in this area. According to our review, no study treated this issue for spare parts demand, except for [64,70].

An alternative forecasting approach that has been applied to spare parts is the one of neural networks. Gutierrez et al. [71] apply a neural network model to 24 time series showing lumpy demand patterns, and their method performed better than single exponential smoothing. Croston’s method and the Syntetos–Boylan approximation. Nonetheless, when a significant decrease in the average of nonzero demand arises between the training sample and the test sample, time-series methods tend to perform better than neural networks. Hua and Zhang [47] propose an application of the support vector machines (SVM) regression method for forecasting spare parts demand (see also [72]). A description of SVM mechanism is reported in [73]. [47] adopt a hybrid logistic regression and the SVM approach aiming firstly to forecast the occurrence of nonzero demands, and then to estimate lead-time demand. Their test over a data set of spare parts demand from a petrochemical company in China suggested this method to perform better than Croston’s, bootstrapping and the method by Hua et al. [74] (described later). A shortcoming of neural network models, however, is the large amount of training data required.

[74] propose a two-step integrated method for spare parts forecasting in process industries. First, the occurrence of a demand for spare parts is estimated as a function of some explanatory variables (they consider plant and equipment overhaul arrangements); the numerical value of demand, then, is assessed through a bootstrapping method. They applied the method to a data set of 40 spare parts from a petrochemical enterprise in China, finding better performance compared to exponential smoothing, Croston and a simple bootstrapping method. The model developed by Ghodrati and Kumar [75], instead, is purely explanatory. To a reliability analysis (to estimate the failure rate of a component) they add a measure of the impact of the working environment and the operators’ skills on spare parts demand. Through a case study, it is shown that including environmental factors in the calculation leads to more accurate forecasts. Unfortunately, very specific information is needed by explanatory methods, as shown by the applications in [74,75]. This information is rarely available, except when the supplier is in charge of maintenance activities at the customer’s, or when the customer itself forecasts its spare part requirements.

Tiben-Lemke and Amato [76] proposed a model in which the failure function of a part (normal wear) is coupled with a prediction of future sales of the related end product in order to determine the amount of replacement parts that will be demanded. The paper also carries out a cost–benefit analysis of collecting information to improve forecasts (in this case knowledge of product failure rates). Yamashina [33], instead, based his model on the calculation of product-still-in-use quantity curves and service part demand curves. Finally, Dolgui and Pashkevich [77] developed a beta-binomial model based on the Bayesian paradigm, which relies on a beta distribution as a prior for the request probability of a group of related stock-keeping units (SKUs) and allows for different demand variance among the SKUs. The model is developed for items with a short demand history.

Given the recent advances in spare parts demand forecasting research, few established results emerge. In the time series stream, most comparative studies supported the superiority of Croston’s method and its variants over traditional time series methods (see for instance, [78]). In particular, the Syntetos–Boylan Approximation (SBA [57]) seems the best performing one according to some studies [57,79], Teunter and Sani [80] instead, suggest that another modification of Croston’s method by Syntetos [81] outperforms the SBA.

Despite this evidence, there is still no conclusive and practitioner-oriented indication on which is “the best” forecasting method for spare parts. First of all, in fact, some studies support the superiority of alternative methods to Croston’s or its variants [61,74,71,52]: no comprehensive testing on a relevant amount of data set was performed to give a conclusive answer on the issue. Second, as [82] point out, results of comparative studies may be biased by the usage of per-period forecast accuracy measures, not suitable for series with many zero demand periods. Inventory and service level measures are suggested as more suited. Nonetheless, the adoption of different metrics in different studies may hamper comparison. Third, most papers propose and evaluate techniques given a generic context of lumpy demand, and only very few propose criteria to differentiate the forecasting methods for different items. Syntetos et al. [31] associate methods to items according to a demand-based classification: the Croston forecasting method (or its variants) should be applied to Intermittent, Erratic and Lumpy items, the SES method to Smooth ones.
Bartezzaghi et al. [69] relate the method suitability to the prevalent source of lumpiness. Kalchschmidt et al. [64] separate stable and irregular demand series through customer disaggregation (filtering), allowing for differentiated techniques. Johnston and Boylan [51] define a threshold of the order interarrival period for which their method is superior to standard EWMA. According to Syntetos and Boylan [10], finally, causal methods (relating demand to other variables) can be used in the initial life cycle phase of a part (since historical data are not available) or when maintenance activities are under control of the vendor or a business customer collecting historical data on some explanatory variables. However, the role of spare parts classification criteria (e.g. the ones discussed in Section 2.1), or of industry-related factors on determining the most suited forecasting techniques have not been thoroughly addressed by research.

Fourth, very few studies concerned the practical applicability of methods to real cases for spare parts management. Requirements and obstacles to the implementation of forecasting methods in real cases, such as data availability, method complexity, users skills, forecasting support systems and so forth have been generally overlooked in academic research.

Eventually, authors tend to acknowledge that traditional single exponential smoothing or moving average are still the most commonly used methods by practitioners [10], and that specific methods and techniques developed for spare parts are still neglected in business practice. However, to our knowledge no extensive empirical study about the diffusion of spare parts forecasting practices in industrial contexts exist, while such studies have been carried out for finished products sales forecasting (see [83] for a review). A partial exception is provided by Cavalieri et al. [84]. In a preliminary study over a sample of 48 companies belonging to the automotive, household appliances and consumer electronics industries, they found out that the majority of companies did not forecast the demand for spare parts, or relied only on judgemental methods. Only the automotive sector had a majority of companies (58%) using a quantitative forecasting method.

2.3. Integrating spare parts classification, demand forecasting with stock control

Spare parts classification and demand forecasting can (and should) be related to stock control policies [4]. Since the amount of inventories due to slow-moving parts is generally important [18,85,86], even small improvements in the management of those items may be translated into substantial cost savings [30].

We here consider the papers analyzed in Sections 2.1 and 2.2 that also address inventory management issues. On the contrary, we exclude from our analysis the very vast amount of literature focusing only on spare parts inventory management. About this topic, we suggest to read seminal papers such as [87,88] or the literature reviews by Guide and Srivastava [89] and Kennedy et al. [17].

Seven papers analyzed in Sections 2.1 and 2.2 [25,36,64,32,37,40,27] develop a decision-making framework considering also inventory management: only three of them [36,37,40], however, do that at a general level. Gelders and Van Looy [25], Kalchschmidt et al. [64], Boylan et al. [32] and Syntetos et al. [27] instead, develop a framework for a specific case study analyzed, a generalization of which is not explicitly proposed. Moreover, some of these works [36,33,44,90] limit their contributions to qualitative guidelines for stock control. Finally, the methodologies by Duchessi et al. [38], Petrovic and Petrovic [42] and Nagar et al. [39] have been implemented into computer programs supporting for spare parts inventory control.

However, the papers quoted above suggest simple and well-established inventory policies, mainly the continuous review (Q, r), with fixed re-order point (r) and fixed order quantity (Q) [25,32,40,27], and the continuous review (s, S), with fixed re-order point (s) and order-up-to level (S) [38,39]. The latter is considered the best-suited technique for low and intermittent demand items by Sani and Kingsman [91]. The other analyzed contributions give only qualitative guidelines on the inventory policies to be adopted. As a matter of fact, as reported by Cohen et al. [92] and Cavaleri et al. [37], few companies (in particular in durable consumer goods industries) apply complex and specific inventory models in practice, primarily due to the mathematical complexity that characterizes their resolution.

This brief review, compared to the spare parts classification and demand forecasting ones above, shows that in the scientific literature an integrated perspective towards spare parts management (classification, demand and inventory management altogether) is often missing or limited. For instance, some of the cited works remain at a too generic level with respect to practitioners’ requirements, while other are designed for a specific case study and are based on a set of rules and/or algorithms tailored for that specific situation, whose generalization to other settings could be questionable.

2.4. The gap between theory and practice in spare parts management

The existence of a gap between research and practice, in the field of demand, inventory and production management has been suggested by previous research [93,13,14,15]. Wagner [13], for instance, observes that “despite half a century of impressive research on inventory modeling … companies have poor customer service despite excessive inventories” and that “incremental mathematical inventory research is not likely to enhance practice”.

Although no extensive studies have been carried out about spare parts management practice, literature suggests that a distance exists between research and practice in this field. Cohen and Agrawal [3], for instance, state that: “Despite the aftermarket’s obvious charms, however, most organizations squander its potential” (p. 130). Wagner and Liedermann [16] studying seven machinery companies point out: (i) a general lack of awareness and investment of time and resources of top management in the spare part business, despite its profit contribution, (ii) the little knowledge companies have of their installed base; (iii) the little use of ad hoc inventory models for spare parts, and (iv) even of the functionalities provided by ERP systems to support forecasting and planning activities.

Syntetos et al. [27] observes that spare parts classification may improve decision-making and constitutes a significant opportunity for increasing spare parts availability and/or reducing inventory costs, but despite its interest for practice, this issue has been overlooked in the academic literature until recently. Boone et al. [11] identify through a Delphi study the main challenges perceived by 18 senior service part managers form different industries. The top three challenges are: the lack of a system or holistic perspective, the inaccuracy of service parts forecast, and the lack of system integration among the supply chain parties. This highlights a strong need of improving the integration of spare parts management processes both at an internal and external level. This issue have been treated by research about the design and management of supply chain and networks (e.g. [94,95]), but little specific research on spare parts supply chains exist. In addition, published case studies show that a rigorous adoption of simple, non-optimized, classification and inventory management methods is enough to provide great benefits to organizations [27,39]. Finally, Zomerdijk and de Vries [96] point out the importance of organizational context for inventory management, criticizing the “one-sided” traditional operations research/operations management approach, and develop an organizational perspective on inventory control.
(considering also the task allocation, communication process, decision making process and people behavior). Their framework is applied to a spare parts management problem, underlining its potential benefits in this field.

The literature review in this section shows that theory about spare parts classification, demand forecasting and integrated spare parts management, despite its (especially recent) advancements, presents some limitations, in particular in the light of its practical applicability. The few empirical studies dealing with spare parts suggest, in addition, the existence of a gap between research and practice.

The rest of this paper is aimed at understanding how this gap is expressed, and at identifying which directions for future research may be drawn to help bridging this gap. This will be done moving from an empirical perspective, as suggested by Boone et al. [11], with specific reference to the durable goods industries, and then by discussing the findings in the light of previous research.

3. Research methodology

We carried out 10 case studies, with the aim of analyzing the level of adoption of spare parts management practices. We chose the cases on a conceptual ground, in order to have a representative sample. In fact, we analyze mass production manufacturing companies providing durable goods addressed to private end users or professional ones, rather than industrial users: the sample companies belong to the automotive, digital printing, heating & air conditioning, household and catering appliances sectors. The case companies have an installed base ranging from a few thousand to several million units, spread in different countries. In addition, these manufacturers manage after-sales networks mostly made by third parties providing technical assistance and spare parts to final customers: the supply chain structure is therefore multi-echelon, with a different number of echelons co-existing in the same supply chain (as in the case described by Kalchschmidt et al. [64]). The direct spare parts customers are not the product end users, but the after-sales network (dealers, repair shops, distributors, wholesalers, etc.). The case companies, therefore, are characterized by a significant supply chain complexity, a medium-to-high responsiveness requirements in spare parts provision (not as high as in some industrial contexts), and a rather wide range of stock keeping units (SKUs) with differentiated demand patterns (slow and fast moving, regular and lumpy). Finally, some of the considered industries, such as the automotive and household appliance ones, are renowned for their state-of-the-art operations management practices (e.g. world class manufacturing, lean manufacturing): in the sample we included some leading players in those industries, that may be supposed to adopt “good” practices also concerning spare parts management. The companies involved in the research identified a key account for the study, in most cases the after-sales logistics manager (at a corporate level, or of the Italian subsidiary). The researchers held a preliminary interview with this person, either by telephone or at the company premises, lasting between 20 min and 1 h, to get an overview of the spare parts range, the structure of the distribution network, and the inventory and demand management practices. Then, a structured questionnaire was sent to the company: the questionnaire and the requested data were filled by the key account or other company managers appointed by the key account. In general, informants included the after-sales managing director and the spare parts warehouse and material planning managers. The data collection concerned: general information on the company, spare parts description (number of codes, classification criteria, volumes, etc.), distribution and customer networks, demand forecasting and inventory management methods and processes, supply chain information sharing and performance measurement systems.

Once the questionnaire was filled, the researchers contacted the companies for explanations and further details, also to get a qualitative feeling on the studied subjects. E-mails, telephone calls and/or face-to-face interviews with the personnel involved allow to gather this supplementary information. Moreover, analysis of secondary sources (such as company documentation and corporate websites) and direct observation (e.g. warehouse tours, access to internal data when possible) were used as supplementary sources of information, ensuring triangulation of data.

The analysis consisted then of data reduction, data display [97], and cross-case comparisons, to identify the main differences and common behaviors among companies [98].

4. Empirical findings

4.1. Sample description

The sample companies belong to different industrial sectors: automotive, household and catering appliances, digital printing, heating and air conditioning. Moreover, they vary in size and headquarters location, as shown in Table 3. Although a global picture of the companies was obtained through the cases, most of the collected evidence concern the Italian organization: six companies are headquartered in Italy (A, B, C, D, E, L) and manage subsidiaries abroad; in cases F, G, H, I, instead, we studied the Italian subsidiary of a multinational company. In these cases, however, Italy is an important market and the Italian after-sales function is in charge of managing the third party after-sales network, as well as spare parts inventories and distribution, at a national level.

Table 4 reports the number of levels of the after-sales logistic network directly owned or managed by the company, while additional levels are generated by the customers’ warehouses. Since most companies have mixed structures (e.g. some regions are served directly by the central warehouse, some others through a regional warehouse), Table 4 reports the highest number of internal levels. Table 4 also reports the role of the warehouse located in Italy and the number and types of customers it serves.

For all companies the majority of customers are repair centers (on average 76% of the total). Repair centers tend to place small orders very frequently and are in general served by express deliveries. On the other hand, wholesalers, importers and subsidiaries are larger customers, often ordering rather high amount of parts with a lower frequency, sometimes creating sudden demand peaks [64].

Table 5 describes the spare parts range managed by the case companies. The average number of SKUs actually kept in stock is about 17,000, with large differences within the sample. Companies A, B, C, D, E, I with headquarters and central warehouse in Italy, move on average 70% of their SKUs. Italian subsidiaries of foreign firms (F, G, H, I) have, instead, a percentage of moved SKUs close to 100%, since the headquarters decided to allocate to the Italian warehouse only “moving” SKUs. Finally, on average, 16% of SKUs make 80% of ordered quantities, although with great differences among companies. For companies D, E and G a very little portion of SKUs (between 2 and 3%) accounts for 80% of volumes, while on the contrary company A, dealing with professional users and having a lower number of parts on stock, make the same volumes with 46% of parts.
4.2. Spare parts classification

As shown in Table 6, six companies out of ten (A, B, D, E, F, I) adopt a simple mono-criterion classification method. Firm C, instead, does not adopt any kind of spare parts categorization for demand forecasting and stock control. It is noticeable that G and H, companies belonging to the automotive industry, adopt a two-criteria and a more structured classification approach than the other sample firms. The most popular criterion is demand volume (or value), adopted by eight firms, followed at distance by part cost (G, H) and part criticality (A, L). None of the other criteria pointed out in Section 2.1 is considered by the case companies.

Among the companies that perform a classification of parts, A is the only one that does not use the demand volumes or value, and relies
demand variation or order interarrival (see [31]) are not assessed. Demand characteristics at a classification level: elements such as firms seem not to carry out any specific evaluation of spare parts. More surprisingly, Section 2.1 are not adopted within the sample. More surprisingly, criteria: more articulated multi-criteria method described in classification methods like ABC, and consider no more than two part criticality criterion (in a non-formalized way) to define the part criticality classification. Together with an ABC classification based on volumes, L adopts company not using a pure quantitative classification methodology is instead on a more qualitative definition of criticality classes, although with little formalization of the classification process. This also reflects the relative low number of SKUs and the relative even volumes for the different SKUs, as commented earlier. The other case companies, in conclusion, prefer simple (quantitative) classification methods like ABC, and consider no more than two criteria: more articulated multi-criteria method described in Section 2.1 are not adopted within the sample. More surprisingly, firms seem not to carry out any specific evaluation of spare parts demand characteristics at a classification level: elements such as demand variation or order interarrival (see [31]) are not assessed. As a consequence, the interviewed professionals answered to questions about the degree of intermittence and lumpiness of spare parts demand, reported in Table 7, through “gut feelings” rather than on the basis of quantitative analysis.

Partial exceptions are the Italian subsidiaries of multinational companies, and in particular carmakers G and H, for which an analysis of demand is carried out at the headquarters, and only medium-to-fast moving codes are kept in stock at the Italian warehouse. Slow-movers are instead delivered directly to customers from the central warehouse: in these cases a low perception of the demand intermittence/lumpiness phenomena at the Italian level seems more appropriate.

4.3. Spare parts demand forecasting

Table 8 shows that firm L does not carry out any kind of forecasting: a pure reactive approach is adopted, with a periodic review of stock levels. Company A, instead, generates forecasts on a purely judgmental basis, and only for parts classified as critical. Companies D and F adopt “black-box forecasting” approaches: forecasts are generated by an information system, but the specific techniques are unknown to the users. Firm D users adjust the forecasting output (the re-order proposals issued by the information system in reason of demand forecasts) for “class A” SKUs. Firm F (the Italian subsidiary of a foreign manufacturer), instead, uses a forecasting, generated at the headquarters, without any local judgmental adjustments.

The other case companies (B, C, E, G, H, I) carry out spare parts demand forecasting with traditional time series methods (e.g. Simple average, Moving average, Exponential smoothing). Company E, in particular, generate forecasts only for “class A” SKUs (then judgmentally adjusted). Firms B and C do not adjust the forecasts, while G, H, I usually do it, even if in different ways. Carmakers G and H receive the forecasts from a European headquarter that centralizes the demand forecasting activity. Italian users may adjust them in reason of their domain knowledge [99]. In the case of firm I, instead, the Italian subsidiary directly generates the forecasts: adjustments may be made on “class A” SKUs.

Although for five companies out of ten a significant amount of spare parts is characterized by lumpy or intermittent demand (see Table 7), no firm adopts techniques specific for intermittent demand (e.g. Croston), because they prefer simpler methods, or simply because they are not aware of the existence of specific

<table>
<thead>
<tr>
<th>Company</th>
<th>Criteria</th>
<th>Methodology</th>
<th>No. of spare parts classes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Demand volume/value</td>
<td>Part cost/value</td>
<td>Part criticality</td>
</tr>
<tr>
<td>A</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>C</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>D</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>E</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>F</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>G</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>H</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>I</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>L</td>
<td>X</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 7
Importance of demand intermittence or lumpiness for the managed spare parts.

<table>
<thead>
<tr>
<th>Consider demand intermittence or lumpiness phenomena:</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very important (50% of SKUs or more)</td>
<td>D, I, L</td>
</tr>
<tr>
<td>Mildly relevant (less than 50% SKUs)</td>
<td>B, C</td>
</tr>
<tr>
<td>Not relevant (very low % of SKUs)</td>
<td>A, E, F, G, H</td>
</tr>
</tbody>
</table>

The “gut feelings” of practitioner attribute to the majority of SKUs intermittent or lumpy demand characteristics (more than 80% for company D). Company C was not able to estimate a % of codes characterized by lumpy or intermittent demand. F, G and H are subsidiaries of large multinationals, keeping on stock mainly medium to fast moving SKUs. Company A manages a low number of SKUs, with no huge differences in consumption (46% of SKUs make 80% of movements; see Table 5). Company F shows an awareness problem
methods. Finally, we can point out that even in the nine companies that carry out a spare parts categorization (see Table 6), there is no differentiation in the forecasting techniques according to the spare part class. Actually, the classification may determine only if a forecasting activity has to be performed rather than how.

4.4. Spare parts stock control

Table 9 shows the re-order policies adopted by the sample companies. A periodic review policy (T, R), is adopted by four companies (A, F, D, I); firms B, G and H, instead, have a continuous review with an order-up-to level (s, S), while a continuous review with economic order quantity (Q, r) is adopted by C, E and I.

Seven companies out of ten keep safety stocks for spare parts: for all SKUs (C, E, H, I), only for the most critical items (A) or for slow moving items (F, L). Companies B, D and G instead do not keep safety stocks.

The inventory management techniques used are rather simple and well established, and not specifically developed for spare parts. Moreover, as we previously noticed for demand forecasting, inventory policies are rather undifferentiated among the different spare part classes.

4.5. Downstream information sharing

In Table 10 we analyze the information sharing with downstream supply chain actors. We notice that almost half the sample shows no information sharing on inventory levels or on demand forecasts even with owned subsidiaries (in particular cases D and I). Coordination with subsidiaries by companies B, E and I removes the uncertainty about when subsidiaries will release orders, but not on the ordered items and quantities. On the contrary, carmakers G and H show a complete information integration between the headquarters and the regional warehouses and also with (at least a significant share of) their authorized dealer network.

Moreover, dealers of companies G and H, through a web platform can check item availability of SKUs unavailable at the manufacturer from other dealers: this visibility encourages lateral transshipments among dealers, improving both efficiency (dealers can reduce inventories of these items) and effectiveness (improved customer service).

5. Discussion

5.1. Summary of findings

Very few empirical studies compare spare parts management practices of companies [16,11,92,84], and little research addressed specifically the existence of a research–practice gap in spare parts management. On the other hand, empirical works pointed out that substantial benefits can be achieved through the adoption of simple but formalized methods [27,39] or of an organizational perspective towards spare parts inventory management [96].

The case studies show little (if any) adoption of ad-hoc methods and techniques for spare parts management in the case companies, the lack of integrated approaches (except for companies G and H), and a rather low level of awareness about how to perform managerial improvements. Fig. 1 summarizes the case findings, focusing on three of the main areas investigated: the adoption of classification methods for spare parts, the adoption of demand forecasting methods, and the information sharing within the internal (between the parent company and subsidiaries/warehouses) and external supply chain (with customers). Fig. 1 highlights the presence and specificity of the management techniques used, as well as the degree of formalization (or specific knowledge for spare parts management) emerging from the cases.

These findings support the idea of the existence of a significant gap between research and practice for spare parts management. Case companies, indeed, are rather representative of the fields of durable goods addressed to private or professional users. In the following, a detailed discussion of the case findings in the light of extant theories is provided, leading to the identification of some directions for future research to address this gap.

5.2. Analyzing the gap between research and practice

5.2.1. Obstacles to the adoption of advanced techniques and methods

For spare parts classification, most of the case companies resort to a traditional ABC method based only on demand volume or value, and rarely consider a second criterion (criticality, cost), in line with findings from Cohen et al. [92]. Notably, no company carries out a categorization based on demand features. Also the actually implemented classifications reported in the literature review in Section 2 are very simple, compared to some complex methods developed by research. Similar evidence was collected about inventory management and demand forecasting, for which no company adopts techniques specifically developed for intermittent demand. This is in line with previous empirical findings [64,84,27]: practitioners, however, lament the inaccuracy of spare

Table 9

<table>
<thead>
<tr>
<th>Inventory policy</th>
<th>Safety stock</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Periodic review (T, R)</td>
<td></td>
</tr>
<tr>
<td>Continuous review (s, S)</td>
<td></td>
</tr>
<tr>
<td>Continuous review (Q, r)</td>
<td></td>
</tr>
</tbody>
</table>

Table 10

Downstream Information sharing.

<table>
<thead>
<tr>
<th>Information sharing</th>
<th>Companies</th>
</tr>
</thead>
<tbody>
<tr>
<td>No</td>
<td>A, C, D, I</td>
</tr>
<tr>
<td>Yes, with company</td>
<td>B, E, I</td>
</tr>
<tr>
<td>subsidiaries</td>
<td>F</td>
</tr>
<tr>
<td>Yes, with the repair</td>
<td>G</td>
</tr>
<tr>
<td>shops/dealer network</td>
<td>H</td>
</tr>
</tbody>
</table>

Fig. 1. Summary of findings from the case studies (the gray area represents cases with little or no formalization, or no specific knowledge of the techniques used).
part demand forecasts [11]. Finally, the distribution of spare parts in the case studies is based on multi-tier networks, in which at least one intermediary exists between the manufacturer and the final customers. The cases confirm findings from Boone et al. [11], that point out the lack of a system perspective in the definition of objectives, leading to sub-optimal decisions, and the low degree of information sharing among suppliers, repairers, customers, and service providers. Case companies lack an integrated view of the supply chain, except for companies G and H, which set up a vertical as well as horizontal visibility of inventories. This integrated view is also scarce in the literature, as pointed out in Section 2.3.

Some reasons can be found for the non-adoption of specific or advanced models, and for the discrepancy between theory and practice. First of all, in particular for demand forecasting, some models proposed in literature are often perceived as too complex by potential users [16]. Moreover, they may be considered too costly to be implemented (investment in skills, human resources or information support tools). In addition, decision-makers are keen to base their decisions on experience and common sense [100]. Therefore managers prefer to rely only on their judgment or on simple models (if they are needed for the large amount of SKUs to be managed). Judgmental forecasting or judgmental adjustments have been debated in research [see 99 for a literature review]. It is known that practitioners tend to use judgemental forecasting as a correction factor of demand forecasts provided by statistical methods, or as the sole forecast basis [101]. Goodwin [101], resorting to previous studies, points out several reasons for that: the perceived slowness of statistical extrapolative methods in reacting to changes, the limited amount of available data, the domain knowledge of human forecasters (e.g. knowledge of events that are going to influence demand in the future), the lack of skills, or the perceived loss of control and ownership when forecasts are delegated to a statistical method. Finally, forecasts or re-order proposals coming out from a method unknown or not understood may be neglected by users [101,102]: this is the “black box” effect experienced by company D.

5.2.2. Analyzing the empirical findings from a contingency perspective

Contingency theory provides a viewpoint for analyzing the gap emerging from the case studies. The contingency perspective [103,104] argues that differences in technological and environmental dimensions result in differences in structure, strategies and decision processes. Therefore, managerial effectiveness can be achieved in more than one way (against a “one size fits all” view), but each way is not equally effective under all conditions [105]: certain organizational actions are more appropriate than others, depending on contextual factors [106]. The contingency perspective has recently gained attention in the operations management domain [107], as a natural evolution of the best practice paradigm [108], and it looks at identifying under which contextual conditions the adoption of operations management practices is effective (see for instance [109]).

Through the contingency lens we analyze the level of adoption of spare parts management practices by the case companies, focusing on: scope of operations (domestic vs. international), firm size (number of employees), strategic context (relevance of the spare parts business), and industry. These contingency variables allow to distinguish between contexts, and show variations in the adoption of practices between the subsamples obtained. Moreover, they are among the main categorical variables found out in the literature review by Sousa and Voss [107]. Our contingency analysis focus on the different degree of adoption of spare parts management practices and tools, rather than on their outcome (performances); thus, it can be classified as a selection form of fit, according to Drazin and van de Ven [110]. Given the kind of research (qualitative, and on a low number of cases compared to the one needed to gather statistical validity), ours has to be considered an exploratory analysis. At an aggregate level, however, it suggests significant differences in spare parts management practices in different contexts. Below, the influence of the different factors is discussed.

5.2.2.1. Scope of operations. Companies headquartered in Italy show a lower degree of adoption of techniques and practices than companies headquartered abroad. In particular, companies with only domestic manufacturing activities (A, B, C, and L) are the ones with the lowest level of practice adoption. Multinational companies with international manufacturing operations, on the opposite, tend to adopt more advanced management practices. This evidence may be justified by the fact that companies with a broader scope of operations have the cultural attitude, resources and tools that may facilitate the process of adoption of spare parts management practices, and it is supported by previous findings on operations management practices (see [107]).

5.2.2.2. Size. All the companies with a lower adoption of practices (A, B, C, L) have a small or medium size (from 135 to 600 employees), while the rest of the sample has a much larger size (7000 or more employees) and a greater adoption of practices. Size, therefore, seems to affect the adoption of spare parts management practices, and this can be explained by the different resource endowment of large versus small firms, and is in line with findings from other contingency research in operations management reviewed in [107].

5.2.2.3. Strategic relevance. Managerial literature stresses the role of after-sales and spare parts business as a low-risk, long-term revenue and profit source, a lever for differentiation, and a source of knowledge on products and customers [3]. From a financial point of view, all the companies declared spare parts margins significantly higher than product margins. Spare parts make from 6% to 14% of Italian revenues for all case companies, except C, which achieves lower revenues (1.4%). Four companies (F, G, H, I) acknowledge a strategic priority on after-sales activities: two of them (G and H) are definitely adopting more advanced spare parts management practices than the rest of the group, while the others (F and I) stand in the middle. On the other hand, firms A, B and C seem to hold onto the old vision of after-sales service as a “necessary evil” [111], and have a poor adoption of practices. More generally, we may argue that all the case companies, to different degrees, are living a transition phase in which higher importance and pressure is put on spare parts management, an area rather overlooked in the past, but their practices, skills and tools are still not adequate (with the partial exception of G and H). This is in line with the findings from Wagner and Liedermann [16].

5.2.2.4. Industry. Automotive companies (G and H) are a step ahead the rest of the sample in managing the spare part business. These companies show a coherent and integrated managerial approach, although they do not resort to sophisticated techniques. This seems consistent with the importance of after-sales to revenue, profit, and competition in the automotive industry [112]. On the other hand, the differences among the other firms seem not to be due to the industry, but rather to the other factors described above. This evidence is in line with a general higher degree of adoption of operations management practices by automotive firms (e.g. lean manufacturing) compared to other industries.
5.2.3. Analyzing the empirical findings from a knowledge maturity perspective

A second approach to deepen the analysis of the empirical findings is through the lens of a knowledge maturity model. This approach is suggested by previous research on inventory management [15]. Actually, the results from the spare parts cases reflect a more general problem of adoption of techniques and tools and of development of organizational processes, that take place gradually with companies as knowledge accumulates within the organization. In Fig. 2, the findings from the cases are categorized into a knowledge maturity model, adapting the maturity stages and management attributes proposed by Niemi et al. [15], based on a previous work [113].

The framework in Fig. 2 identifies five maturity stages. According to Niemi et al. [15], at the Initial stage the organization possesses no specific knowledge on the subject (in our case spare parts management); tacit knowledge and assumptions on basic causalities are instead present at the Awareness stage. Knowledge is made explicit at the Establishment stage, causalities are expressed quantitatively at the Quantitative Management stage, and they are finally thoroughly understood at the Optimization stage. The three attributes represented in Fig. 2 are: the technical tools (planning tools and operative data systems) used to carry out the spare parts classification, demand and inventory management tasks, the skills, roles and responsibilities of the operators carrying out those tasks, and the performance measurement and incentive systems related to spare parts management.

More than half the companies have only local planning tools with no advanced functions (B, D, I) or tools are even absent (A and L for forecasting, C for inventory). E and F use the company ERP systems for basic planning functions, while G and H adopt ad-hoc planning tools linked to the ERP system. The specific skills for spare parts management appear to be deficient or basic in many companies (i.e. some companies have little knowledge about the lumpiness phenomenon and most do not know about the existence of specific forecasting methods for spare parts). In companies A, B, C, L the roles involved are those of operators (see [15]), mainly dealing with day-by-day activities (control of deliveries and ordering processes) with low emphasis on planning activities. The operator task is supported by an expert in companies D, E, I (at the Italian level), and F (at the European level). For companies G and H, expert roles at the European level define the policies followed by operators at the Italian level. Finally, the focus on measurement systems is varied, as illustrated by Fig. 2, with some kind of incentive systems in companies F, D, G, and I.

From Fig. 2 it is possible to infer a low maturity for companies A, B, C and L, corresponding to an "awareness" stage. Companies D, E, F and I, although through different paths and with different weaknesses, are moving into an establishment of their spare parts management practice. Only companies G and H lean towards a higher maturity of the spare parts management process (quantitative management), although ad hoc and optimization techniques are not yet in place.

6. Bridging the gap: directions for future research

Building on the previous discussion, we propose four main directions for future research, aimed to bridge the gap between research and practice in the area of spare parts management.

(1) Developing an integrated approach to spare parts management: Some limitations of the models proposed in literature have been pointed out in Sections 2 and 5. However, a major problem stands in the paucity of research with an integrated perspective on spare parts management. Wagner and Liedermann [16] found out only two papers on operations strategy and design for spare parts management, contrasted to a plethora of literature at the planning and operational levels. Here we argue that an approach integrating spare parts classification, demand management, and forecasting, inventory management models and performance measurement is hardly present in literature (some partial examples are reported in Section 2.3). We suggest that research develop frameworks encompassing all these aspects. The adoption of an integrated view, as depicted in Fig. 3, is one of the main aspects affecting the overall effectiveness of spare parts management in companies, leaving aside the complexity of the specific techniques used; at the same time the absence of an integrated view is one of the main gaps reported in the literature of their spare parts management.

![Fig. 3. An integrated approach to spare parts management.](image-url)

![Fig. 2. Application of a knowledge maturity model to the case companies.](image-url)
analyzed cases. The integrated perspective suggested in Fig. 3 stresses the relation between the steps of spare parts classification, demand forecasting and inventory management, and the subsequent performance measurement. Decisions on these aspects should be made with a systemic perspective, and with a differentiated approach, where different kinds of parts (according to the classification step) are treated with different demand and inventory management techniques.

(2) Developing contingency-based managerial guidelines: To our knowledge, no contingency research about spare parts management practices has been carried out. Extensive research should be undertaken in this perspective. It may serve different purposes, in line with the different approaches to contingency research [107, 110]: (a) to verify, at a single practice level, the relation between contextual factors, such as the ones analyzed in Section 5.2.2, and the adoption of spare parts management practices (selection approach); (b) to study how the interaction between contextual factors and spare parts management practices affects performances, for single factors (interaction approach) or with a holistic perspective (system approach); (c) to derive normative indications and guidelines for company managers, for instance indicating the practices that can bring substantial benefits under specific conditions as in [109]. The analysis carried out in this paper is not sufficient to give normative indications to company managers. However, our research pointed out, for instance, that firms from other industries mass-producing goods may look at practices in the automotive sector as a reference point. As well, confirming previous findings [3, 16], strategic commitment appears as a fundamental pre-condition to improve spare parts management. Finally, small firms, not surprisingly, show a low adoption of spare parts management practices. The definition of a development path for small firms on how to gather the necessary skills (e.g. by cooperating with non-competitive firms operating in the same or similar industries) and to adopt the best suited practices for their context should be the aim of future studies.

(3) Favouring the knowledge accumulation process: As pointed out by Zomerdijk and de Vries [96], the organizational aspect is of utmost importance for the success of the implementation of management techniques in companies. Müller-Merbach [114] reckons that scholars in operations research and management science tend to neglect the implied process, i.e. the approach to reality. Therefore, while adopting an integrated approach and having identified which practices are more effective under given conditions, researchers (and practitioners as well) should ask themselves how this translates into decision-making processes, task allocation, communication processes and how it is affected by personal behaviors of people involved [96]. Tools such as the knowledge maturity model introduced in Section 5.2.3 can be an important contribution of research to managerial practice. Efforts should be devoted to further refining such knowledge maturity model for the specificity of the spare parts field, in order to provide companies with an instrument to understand their current state of maturity in spare parts management. As well, general transition paths for the different managerial attributes should be developed. In addition, such kind of models may serve as diagnostic tools to identify the weaknesses and prioritize actions for the development of management attributes in real companies (e.g. skills development, IT systems adoption, etc.). Finally, such a research stream should investigate the relations between different management attributes, drawing inspiration from works in other operations management fields and grounding concepts on in-depth case studies. For instance, the relation between IT tools for spare parts management and operators’ skills and responsibilities, as well as the way in which performance and incentive systems may facilitate the increase of knowledge into the organizations are topics worth research interest.

(4) Supplementing models with practical relevance: Despite some criticism emerging from this discussion, we believe that research must continue to pursue innovative, improved, and sometimes complex quantitative models for spare parts management. Nonetheless, a great effort should be devoted to evaluate how these models can be taken into practice. So, researchers should focus on the assessment of the benefits achievable by organizations applying such models [115]. As well, the requirements and conditions for their practical applicability, such as data availability, users’ skills, information support systems and so forth, have to be addressed. We encourage the use of the case study method for these purposes, as well as to facilitate the transferability of the developed solutions.

In addition, the impact of (upstream and downstream) information sharing (e.g. about demand and inventories) and the organizational challenges for its implementation should be addressed, with particular reference to the supply chain structures depicted by the case studies in this paper: multi-echelon, with a large and differentiated customer base. In such contexts, as for global operations, the challenges of supply chain integration are great [116], but worth the effort since they can improve supply chain performance [95, 117]. We already noted in the literature review that the way information sharing affects demand forecasting accuracy is a topic under-investigated by research. As pointed out by Martin et al. [70], also the way local advance information (e.g. about product usage conditions) can be exploited in order to improve planning decisions should be addressed.

7. Conclusion

Despite the increasingly relevant role of spare parts management in durable goods industries and its related challenges [3], the research and business communities did not devote great attention to the issue until recently. Very few studies, indeed, focus on reviewing the state of the art of research advancements in this field [17, 89, 94], or on analyzing managerial practices [92] and the discrepancies with research [16]. The contribution of this paper moves along these two directions, reviewing research on spare parts and carrying out and discussing a multiple case study. As a third element of contribution, the paper provides indications for future research.

First of all, a comprehensive literature review on research about spare parts categorization, spare parts demand forecasting, and their integration with inventory management approaches was undertaken. The review in Section 2 adds to the existing knowledge since it provides a systematic analysis of the research contributions on these topics, identifying some research gaps, such as the little attention about when the proposed methods are superior to others and should be applied, and the lack of an integrated perspective to the problem.

Secondly, we performed ten case studies in various sectors (automotive, household appliances, printing systems, heating and air conditioning). The empirical evidence supports the hypothesis put forward by previous works [3, 11, 16] of a gap between the models and methods developed by research and their actual adoption in business practice. The analyses in Section 5 gave a further contribution by exploring possible causes for this gap, at three levels: the limitations of the proposed models in the perspective of their practical adoption, the role of contingency factors in explaining different levels of adoption of spare parts
management practices in the sample, and the level of maturity of spare parts management in the studied organizations.

The third contribution of the paper stands in the identification of four streams for future research in order to bridge this gap, presented in Section 6. A major effort should go towards the definition of research frameworks with an integrated perspective on spare parts classification, demand forecasting, inventory management and performance measurement: such a perspective has surprisingly been overlooked by both research [16] and practice [11]. Such frameworks should allow to appreciate how management practices or policies at one of these levels influence the choices and their effects at other levels, and also to promote the adoption of differentiated approaches (i.e. to different kind of parts may correspond different management techniques).

A second indication for research concerns the application of the contingency approach to spare parts management, in order to appreciate the effectiveness of managerial practices in relation to contextual factors, and to subsequently develop normative models. Third, the refinement and adoption of knowledge maturity models as diagnostic tools can indicate to companies their state of maturity in spare parts management, and identify or prioritize development actions. A fourth and final suggestion regards research on modeling aspects (e.g. demand forecasting methods), which should increase the emphasis on understanding the requirements for practical applicability (e.g. data needs, required skills) and on assessing the possible benefits of methods, resorting also to case study applications.

Besides some merits, this research work presents important limitations. Although it gave the opportunity to discuss all the above issues, the set of case studied does not allow to generalize our empirical findings: for that aim, a survey research is required. Moreover, the sample cases present two other limitations: firstly, the differences in size, industry and other firm characteristics, although allowing to explore the effect of these aspects, may hamper a direct comparison among the companies. Secondly and more importantly, a true best practice case is missing. Although this is itself a result of the empirical research (some of this companies are leading in industries with quite advanced practices in direct manufacturing and logistics), it also constitutes a serious limitation of the paper, since we lack a reference point for appreciation the effectiveness of managerial practices in relation to contextual factors, and to subsequently develop normative models. To overcome these limitations, more empirical research should be carried out, as called by Syntetos et al. [27], both through the survey and vertical case study methods, but this is also part of the directions for future research presented in the previous section of this paper.

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References

Gutierrez RS, Solis AO, Mukhopadhyay S. Lumpy demand forecasting using

Bao Y, Wang W, Zhang J. Forecasting intermittent demand by SVMs regression. In: IEEE international conference on systems, man and cyber-
netics, p. 461–6.


Hua ZS, Zhang B, Yang Y, Tan DS. A new approach of forecasting intermittent

Ghodrat B, Kumar U. Operating environment-based spare parts forecasting and

Tibben-Lemke RS, Amato HN. Replacement parts management: the value of

Dolgui A, Pachkevich M. Demand forecasting for multiple slow-moving items with short requests history and unequal demand variance. Interna-

Willemin TR, Smart CN, Shockor JH, DeSaeteths PH. Forecasting intermittent

Syntetos AA, Boylan JE. On the stock control performance of intermittent


Zotteri G, Kalchschmidt M. Forecasting practices: Empirical evidence and a

Cavaleri S, Perona M, Pinto R, Saccani N. After service sales in durable


Verrecke A, Verstraeten P. An inventory management model for an inventory

Silver EA. Some ideas related to the inventory control of items having erratic demand patterns, 1970, CORS, 8, 87100.


Guide DR, Srivastava R. Repairable inventory theory: models and applica-

Dekker R, Bayindir ZP. Spare parts inventory control: an overview of issues for a large industrial complex. IMS International Forum-2004 Global

Sani B, Kingsman RG. Selecting the best periodic inventory control and
demand forecasting methods for slow demand items. Journal of the Opera-


Georgiadis MC, Tsaiaks P, Longinidou SF, Sofoglou MK. Optimal design of

Kim KK, Byoo SV, Jung MD. Inter-organizational information systems visibility in buyer-supplier relationships: the case of telecommunica-


Kalchschmidt M, Zotteri G, Verganti R. Inventory management in a multi-

Kalchschmidt M, Verganti R, Zotteri G. Forecasting demand from hetero-


Fishler ML, Raman A. Reducing the cost of demand uncertainty through

Fishler ML, Hammond JB, Obermeyer WR, Raman A. Making supply meet

Bazzaghi E, Verganti R, Zotteri G. A simulation framework for forecasting


Gutierrez RS, Solis AO, Mukhopadhyay S. Lumpy demand forecasting using