Advances in spare parts demand forecasting on industrial applications: a systematic literature review

Avanços na previsão da demanda de peças de reposição em aplicações industriais: uma revisão sistemática da literatura

Avances en la previsión de la demanda de repuestos para aplicaciones industriales: una revisión sistemática de la literatura

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Saymon Galvão Bandeira, Discente da Universidade Federal de Goiás, Faculdade de Ciências e Tecnologia, no Programa de Pós-Graduação em Engenharia de Produção
https://orcid.org/0000-0002-3715-341X

Symone Gomes Soares Alcalá, Professora da Universidade Federal de Goiás, Faculdade de Ciências e Tecnologia, no curso de Engenharia de Produção e no Programa de Pós-Graduação em Engenharia de Produção
https://orcid.org/0000-0001-9783-6506

Rui Alexandre de Matos Araújo, Prof. Associado no Departamento de Engenharia Eletrotécnica e de Computadores, Institudo de Sistemas e Robótica, ARISE, da Universidade de Coimbra.
https://orcid.org/0000-0002-1007-8675

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Abstract

Objective: To study the forecasting of demand for spare parts in the industry.

Methodology: This article presents a systematic literature review of the current state of the art in real-world applications related for forecasting spare parts demand in industry. High-quality articles are selected, and visualization and analysis tools are used to inspect the selected works. A bibliometric analysis is also performed to reveal trends.

Originality/Relevance: Forecasting spare parts demand is an important task across many industries, as inventory costs can account for 60% of total costs. However, the choice, evaluation, and application of an appropriate forecasting approach remain challenging. This is mainly because spare parts demand exhibits intermittent behavior, characterized by demand at widely spaced time intervals and highly variable demand sizes; therefore, forecasting spare parts demand is a complex task.

Main results: The main results reveal the predominant industrial sectors, applications with intermittent items, and non-parametric approaches. Furthermore, the findings reveal gaps in the evaluation of forecasting approaches and perspectives that can be adopted in practice.

Keywords: Spare parts; forecasting; industry; systematic literature review; real-world applications.

Resumo

Objetivo: Estudar a previsão da demanda por peças de reposição na indústria.

Metodologia: Este artigo apresenta uma revisão sistemática da literatura do atual estado da arte das aplicações do mundo real relacionadas à previsão da demanda por peças de reposição na indústria. Artigos de alta qualidade são selecionados, e ferramentas de visualização e análise são usadas para inspecionar os trabalhos selecionados. Uma análise bibliométrica também é realizada para revelar tendências.

Originalidade/Relevância: A previsão da demanda por peças de reposição é uma tarefa importante em muitas indústrias, já que os custos de estoque podem representar 60% dos custos totais. No entanto, a escolha, avaliação e aplicação real de uma abordagem de previsão apropriada ainda são desafiadoras. Isso ocorre principalmente porque a demanda por peças de reposição tem comportamento intermitente, que é caracterizado pela ocorrência de demandas em intervalos de tempo muito espaçados e tamanhos de demanda altamente variáveis, portanto, a previsão da demanda por peças de reposição é uma tarefa complexa.

Principais resultados: Os principais resultados revelam os setores industriais predominantes, aplicações com itens intermitentes e abordagens não paramétricas. Além disso, as descobertas revelam lacunas em relação à avaliação de abordagens e perspectivas de previsão que podem ser adotadas na prática.

Palavras-chave: Peças de reposição; previsão; indústria; revisão sistemática de literatura; aplicações no mundo real.

Resumen
Objetivo: Estudiar la previsión de la demanda de repuestos en la industria.

Metodología: Este artículo presenta una revisión sistemática de la literatura sobre el estado actual de las aplicaciones prácticas relacionadas con la previsión de la demanda de repuestos en la industria. Se seleccionaron artículos de alta calidad y se utilizaron herramientas de visualización y análisis para examinar los trabajos seleccionados. También se realizó un análisis bibliométrico para identificar tendencias.

Originalidad/Relevancia: La previsión de la demanda de repuestos es una tarea importante en muchas industrias, ya que los costos de inventario pueden representar el 60 % de los costos totales. Sin embargo, la elección, evaluación y aplicación de un enfoque de previsión adecuado sigue siendo un desafío. Esto se debe principalmente a que la demanda de repuestos presenta un comportamiento intermitente, caracterizado por la aparición de demandas en intervalos de tiempo muy amplios y con volúmenes de demanda muy variables; por lo tanto, la previsión de la demanda de repuestos es una tarea compleja.

Resultados principales: Los resultados principales revelan los sectores industriales predominantes, las aplicaciones con artículos intermitentes y los enfoques no paramétricos. Además, los resultados revelan deficiencias en la evaluación de los enfoques y perspectivas de pronóstico que pueden adoptarse en la práctica.

Palabras clave: Repuestos; prognóstico; industria; revisión sistemática de la literatura; aplicaciones prácticas.

1. Introduction

In the era of high process digitization, driven mainly by Industry 4.0 initiatives (Frank et al. 2019), planning activities can be improved by insights from data-driven methodologies. Such activities can be challenging in industry due to the nature of available data. Spare parts providers frequently must forecast the demand for Stock Keeping Units (SKUs) to maintain suitable inventory levels and, as a consequence, improve service to their customers. The challenges related to this scenario can be increased by intermittent items, which are prevalent in service sectors (Babai et al., 2019; Alalawin et al., 2020). As noted by Hong et al. (2023), in some industrial sectors, up to 60% of spare parts can exhibit intermittency.

Spare parts demand forecasting for intermittent items is a complex task due to their nature. In general, spare parts with this profile are characterized by high-spaced time intervals and highly variable demand sizes. Although forecasting methods have been developed in the literature to handle this (Croston, 1972; Babai et al., 2019), other types of items can reveal diverse underlying patterns where specialized methods for intermittency may fail. That is, spare parts forecasting in the industry can be challenging for new researchers or professionals due to the massive possibility of scenarios and the diversity of demand patterns, forecasting approaches, evaluation methodologies, etc. Furthermore, as manufacturers are affected by the bullwhip effect, demand information can help to address this problem (Frank et al. 2019).

In the literature, review works on spare parts management can be found to support future research, though they often focus on specific topics. For example, Bacchetti and Saccani (2012) explored the gaps between research and practice by reviewing forecasting methods, classification frameworks, and inventory models applied to spare parts by analyzing ten use cases. Although the review provided good empirical evidence of gaps in the literature, the reported cases may not be generalizable to other use cases. A review of inventory models by Bounou et al. (2017) focused on probabilistic models, providing valuable insights into their application and use in the context of spare parts. Inventory models are essential for decision-makers when managing stocks. However, the integration of forecasting methods with inventory models lacks investigation. Another review by Van Der Auweraer et al. (2019) covers a more recent approach for spare parts forecasting: installed base information. The work introduced many concepts and approaches for installed base forecasting, but a large-scale study could pose significant challenges.

The application of bootstrapping methods is investigated in the study of Hasni et al. (2019). The work provides insights into bootstrapping approaches, related properties, and assumptions about practical applications. Furthermore, the study focuses only on a detailed description of bootstrapping-based methods for spare parts. In the study of Kulshrestha et al. (2024), a review of spare parts management in the context of Industry 4.0 was given. They found that the emergent technologies of Industry 4.0 provide greater visibility into database-based approaches such as Artificial Intelligence, reducing production costs and improving profitability and reliability. A review of intermittent forecasting methods applied to spare parts was introduced by Pinçe et al. (2021), which provides a quantitative analysis of the performance of the proposed methods. However, the study lacks analysis for nonintermittent items.

In this context, this work conducts a systematic literature review (SLR) of forecasting applications in industry, focusing on real-world studies on spare parts forecasting. Papers with real-data applications are selected for their more realistic results, approximating purely theoretical contributions to applied practice. The focus is on discovering the main demand forecasting approaches, industrial branches, evaluation metrics, challenges, and characteristics of spare parts. To accomplish this, a bibliometric analysis is conducted using data from Science Direct, IEEEXplore, Springer, Web of Science, and Scopus. An overview of the current state-of-the-art in spare parts demand forecasting is provided. This is done by systematically examining the papers after applying selection criteria and extracting pre-determined data fields. The SLR findings reveal gaps regarding the evaluation metrics for forecasting models and the practical adoption of forecasting approaches.

This work does not only analyze forecasting works with intermittent items but also with non-intermittent items, seasonality, trend, and stationary characteristics. Thus, it covers a broader scope of work and provides insights into the challenges faced in various industrial applications. Furthermore, none of the state-of-the-art reviews employs the SLR methodology, as in the current study. The SLR can extract gaps and trends in the proposed research topic to support future studies (Kitchenham, 2012). Thus, this review provides background on the methodologies available to new researchers, offers possible directions for experienced researchers and professionals, and presents the current state of the literature.

The remainder of this paper is organized as follows. Section 2 describes the methodology used in this review. Section 3 presents the results of the bibliometric analysis. In Section 4, an overall description of the main forecasting methods, applications, practices, evaluation metrics, and trends is presented. Section 5 concludes this work, summarizing the findings and outlining future directions.

2. Methodology

An SLR is a study to identify, analyze, and interpret evidence about a specific research question. Besides, a systematic review can identify key scientific contributions to a particular field or research question (Tranfield et al., 2003). It can be done by using a methodology that can certainly be reproduced. Additionally, an SLR is a fundamental tool in academic research, as it allows for a comprehensive analysis of the available evidence on a given research topic. A replicable methodology ensures that all relevant sources are considered, minimizing bias and providing a consolidated, critical view of existing knowledge. This work adopts the SLR methodology discussed by Kitchenham (2012), detailed in the following subsections.

2.1. Research Questions

The first stage of the current SLR was to define the research questions. They delimit the scope of the research, help avoid dispersion into irrelevant topics, and aid in selecting appropriate methodologies. This definition is useful for delimiting the scope of the work and providing directions for subsequent stages. The research questions are presented below:

- RQ_1: What industrial applications are subject to spare parts forecasting?
- RQ_2: What methods are being used to perform spare parts forecasting?
- RQ_3: How are the proposed approaches evaluated, and what metrics are the used?
- RQ_4: Which characteristics are present in spare parts data and its related challenges?

Since the research questions RQ_1 to RQ_4 were defined, one can set the required search parameters for the scientific work databases.

2.2. Search Procedure

To cover most of the literature on spare parts forecasting, five scientific databases were selected for analysis: Web of Science (WoS), Science Direct, IEEEXplore, Springer, and Scopus. Researchers widely use these databases, making available high-quality papers submitted to peer-reviewed processes in most cases. For each database, the keywords “spare parts” combined with the terms “demand”, “forecasting”, “prediction”, “method”, and “model” were searched in the field title or abstract. The period of publications was restricted to 2010-2024 to favor the most recent results. Furthermore, only research articles were selected.

At the end of the first search, 353 papers were obtained. A merge activity was performed on results from different databases to remove duplicate documents. Besides, the results (database for analysis) were stored in the formats XLSX and RIS, both generated with Zotero (Zotero, 2024), a software tool for bibliography control. The search was carried out on July 15, 2024. Next, the papers were systematically analyzed to retain only those within the scope of the SLR.

2.3. Selection Criteria

Additionally, some selection criteria were applied to the remaining studies. Such criteria are useful for picking only high-quality papers and studies aligned with the SLR goals. To accomplish this, the Title, Abstract, and Introduction sections were verified considering the following:

- SC_1: The study considered spare parts data.
- SC_2: The work was focused on forecasting.
- SC_3: The approaches were evaluated using data from real-world problems.
- SC_4: The study considered data from the industry.

The criteria above were helpful because, for example, in most cases, the work focused on inventory models (which are closely related to forecasting); however, this subject is out of scope. If any criteria were not met, the paper would be discarded. After that, 63 works were selected to compose the final base for study and analysis. Figure 1 illustrates the processes performed during the SLR.

As noted, in Figure 1 a bibliometric analysis was performed and is detailed in the following sections.

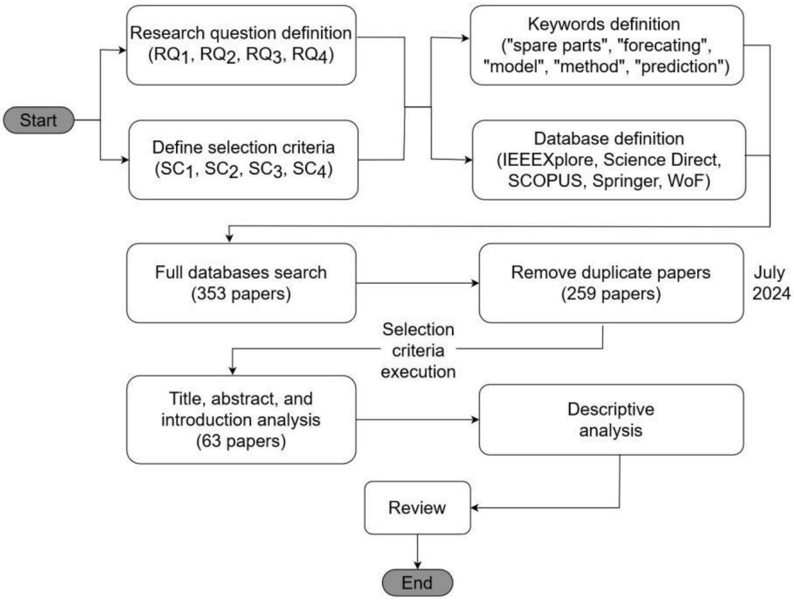

Figure 1: Methodology of SLR: Performed processes.

3. Bibliometric analysis

A Bibliometric Analysis is a form of study aided by computer tools that identifies the central aspects of a specific research topic. Such aspects can be the most influential journals, papers, methodologies, authors, etc. In the following subsections, the current SLR results are presented.

3.1. Publications Distribution

According to the SLR results, the selected works are distributed in 43 journals. Figure 2 shows the distribution of papers among them. Most publications are in the International Journal of Production Economics (IJPE) and the European Journal of Operational Research (EJOR), with 20.63% and 4.67% of papers, respectively. The main areas of interest in the journals are continuous optimization, decision support, computational intelligence, production, manufacturing, logistics, and general developments in the operational research field and decision-making processes. In addition, some journals focus on mathematical modeling processes, microsystems technology, and nanotechnology for industrial applications.

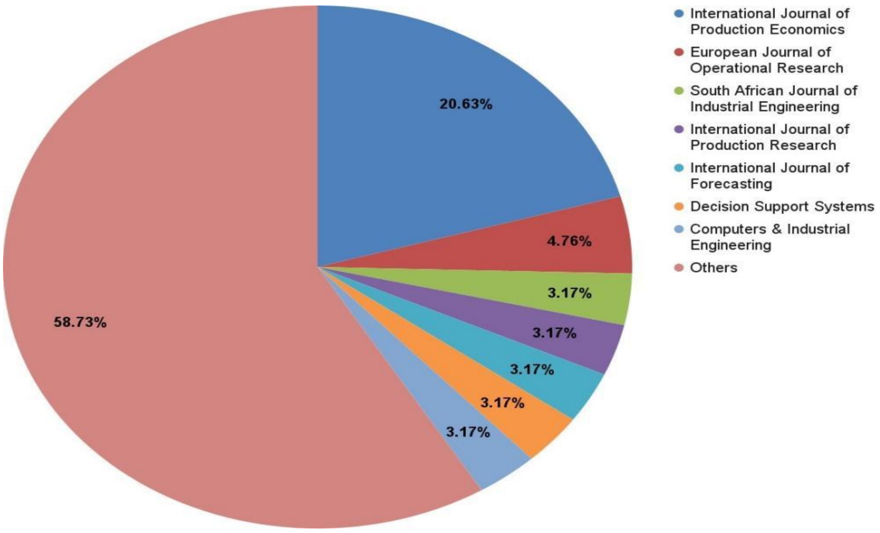

Figure 2: Distribution among journals

In Figure 2, the "Others" slice represents journals with no more than one publication. It should be noted that many journals fall into this category, suggesting a reasonable number of spare parts forecasting studies. Figure 3 presents the distribution of publications from 2010 to 2024.

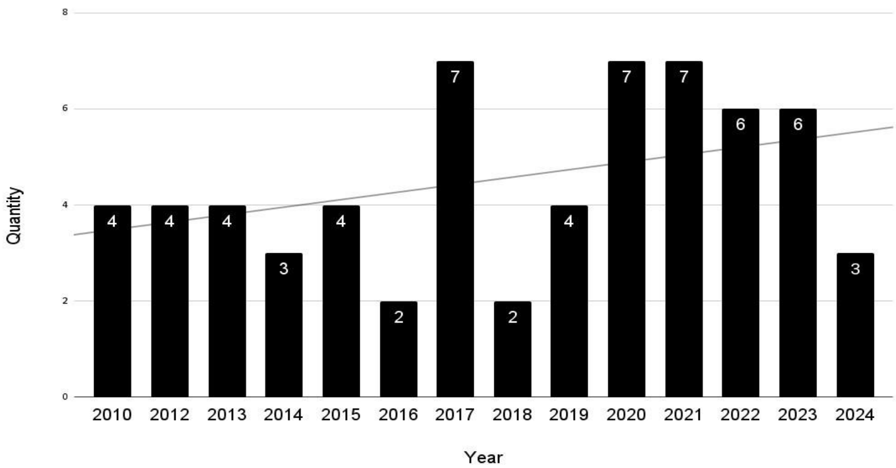

Figure 3: Distribution by year: Number of publications from 2010 to 2024.

According to Figure 3, although the number of publications in 2022 and 2024 remains unchanged, the trend line indicates an increase in the number of studies. This may reflect a growing interest among the scientific community in spare parts forecasting in a context more closely aligned with industrial applications.

3.2. Relevant Publications

Papers can also be analyzed by counting the number of times they are mentioned (i.e., citation analysis). The Open Citations platform (Peroni and Shotton, 2020) was chosen and used to determine the number of citations for each paper selected in this SLR. The citation analysis produced a list of 10 papers with the most citations. These results are reported in Figure 4.

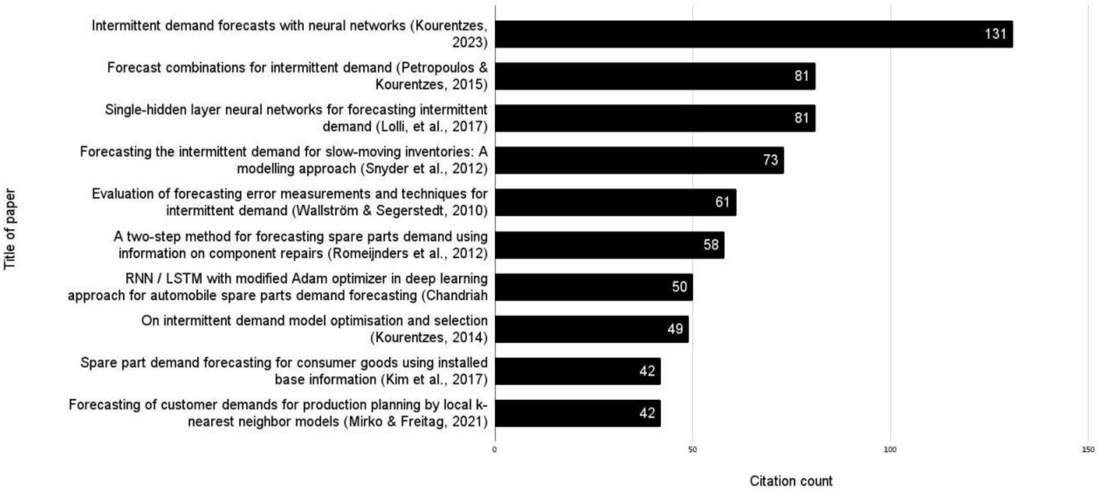

Figure 4: *Most cited papers: top 10 works.*

The most cited paper, “Intermittent demand forecasts with neural networks” by Kourentzes (2013), proposes an ANN method for forecasting spare parts with intermittent demand. On the other hand, “Forecast combinations for intermittent demand” by Petropoulos and Kourentzes (2015) is the second most cited paper and provides new directions (a combination approach) for the forecasting problem. It should be noted that many other papers focus on intermittent demand items (Rego and Mesquita, 2015, Moon et al., 2012, Kück and Freitag, 2021).

3.3. Methods Frequency

According to the research question RQ_2 defined in Section 2, information on the applied forecasting methods was extracted. A wide range of methodologies, totaling 73 approaches, was found in the literature. Table 1 presents the most frequent methods; the "paper for reference" column provides additional details.

It should be noted that the methods listed in Table 1 appear in at least 10% of the papers selected for this SLR. Furthermore, there are many variants of specific approaches, some of which were grouped for simplification. For example, Exponential Smoothing could be its simplest form, or a variant designed to handle trend or seasonality. A brief description of these forecasting methods is given in Section 4.

Table 1:
Most frequent methods

Forecasting method	Amount of works	Paper for reference
Exponential smoothing (ES)	39	(Babai et al., 2020)
Syntetos and Boylan approximation (SBA)	25	(Babai et al., 2019)
Croston's method (CR)	25	(Croston, 1972)
Artificial neural network (ANN)	24	(Lolli et al., 2017)
Autoregressive integrated moving average (ARIMA)	15	(Gamberini et al., 2010)
Moving average (MA)	15	(Romeijnders et al., 2012)
Teunter-Syntetos-Babai (TSB)	11	(Babai et al., 2014)
Random forest (RF)	10	(Breiman, 2001)
Naïve forecasting (NV)	7	(Petropoulos et al., 2016)
Linear Regression (LR)	7	(Choi and Suh, 2020)

3.4. Methods Frequency

An important factor of concern when proposing new approaches is how to evaluate them. The purpose of RQ_3 is to identify how the authors assess each method's forecasting ability. Again, a wide range of precision metrics (59 in total) was identified, and Table 2 presents the most frequent evaluation metrics. More details on the use of these metrics are provided in Section 4, along with some recommendations.

Table 2
Most frequent evaluation metrics.

Evaluation metric	Percentage of works
Root mean squared error (RMSE)	10.92%
Mean absolute percentage error (MAPE)	10.34%
Mean squared error (MSE)	10.34%

Mean absolute error (MAE)	8.62%
Mean error (ME)	8.05%
Mean absolute scaled error (MASE)	6.32%

3.5. Industrial Branch

Since the scope of this SLR was delimited to real-world problem applications, the specific industrial branch of each paper was extracted, as defined in RQ_1. The main purpose of this research question is to identify which industrial branches are subject to forecasting applications, the challenges associated with each branch, and whether there is a predominance among them. The results are shown in Figure 5.

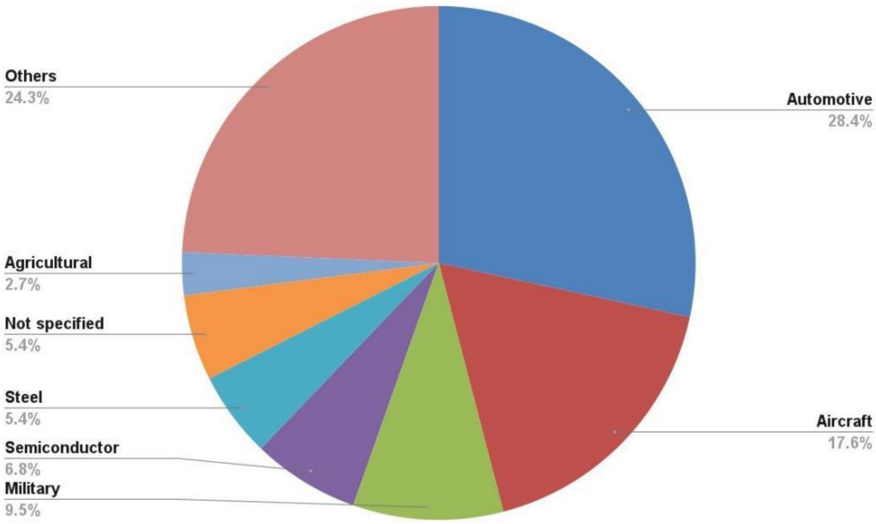

Figure 5: *Main industrial branch applications.*

A total of 22 different industrial branches were found. As presented in Figure 5, the automotive and aircraft sectors have been the focus of researchers, which may reflect the emergent necessity for companies. Indeed, at the retailer or wholesaler level, the automotive and aircraft sectors are highly affected by service parts, characterized by intermittent patterns (Babai et al., 2014). Such items usually represent a large proportion of SKUs.

Besides that, intermittent items (detailed in the following subsection) are more difficult to forecast because they are characterized by infrequent arrivals and highly variable demand sizes. The forecasting methods shown in Table 1 reinforce this, in the sense that most of them were designed/modified specifically to predict intermittent and/or obsolescence (decreasing trend in demand value) patterns, as in the case of Croston's method (CR), Syntetos and Boylan approximation (SBA), and some Artificial Neural Networks (ANN) based approaches.

3.6. Spare Parts Data Characteristics

A specific spare parts demand characteristic was identified in most of the studies selected for this SLR: intermittency. This is an issue of RQ_4, whereas the authors reported other demand patterns. The relevance of the design for forecasting approaches for intermittent items was identified when creating a network of keywords co-occurrence, as shown in Figure 6.

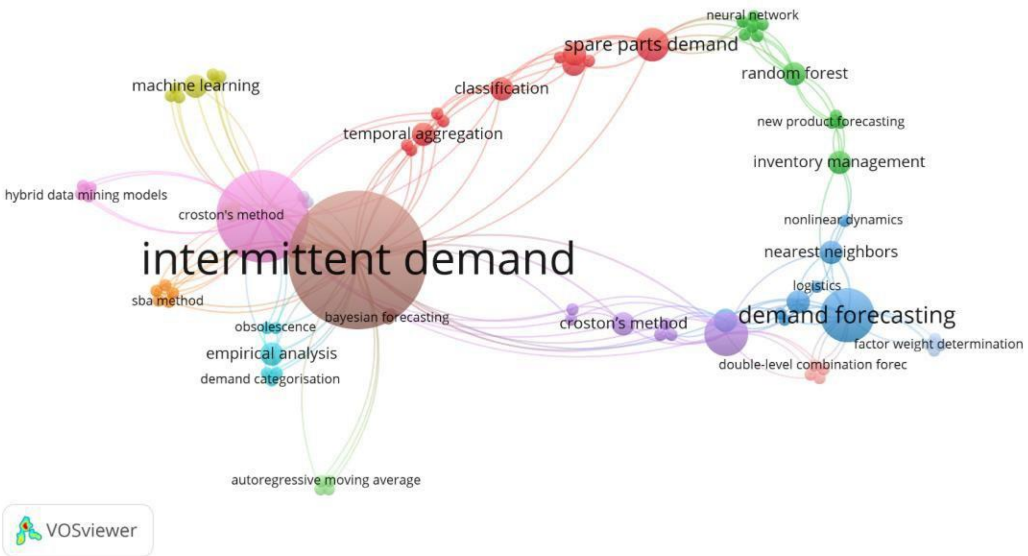

Figure 6: *Keywords co-occurrence network found in spare parts forecasting.*

In Figure 6, the links between specific nodes indicate the strength of the relationship based on the number of occurrences in the same study, and the size of each node represents its frequency. The "intermittent demand" keyword occurred 14 times, according to this SLR. However, this is not the only type of demand reported in the literature. A further analysis was performed to investigate the other types of spare parts demands, if any. This was done by recording the kind of demand specified as the papers were analyzed.

A discovery was the possible convergence of the use of some terms to categorize the demand patterns conforming to the framework proposed in (Syntetos et al., 2005):

- Intermittent (36 occurrences): large inter-demand intervals and more regular demand sizes.
- Lumpy (14 occurrences): large inter-demand intervals and high demand size variability.
- Erratic (13): small inter-demand intervals and high demand size variability.
- Smooth (8): small inter-demand intervals and more regular demand size.

The framework initially intended to define theoretical cut-off values for inter-demand intervals and demand size, for which CR or SBA is expected to achieve higher forecasting accuracy (Syntetos et al., 2005). Finally, other terms were used to categorize the demand patterns, which are most common across different research areas (such as Econometrics). For example, some works applied methods explicitly designed to extrapolate seasonal, cyclic, or stationary time-series (Matsumoto and Ikeda, 2015; Guo et al., 2017; Kim et al., 2017; Sareminia and Amini, 2023).

4. Results analysis

This section presents a detailed description of the main results of SLR. In Subsection 4.1, a background on forecasting methods is provided, including practices, usage tips, advantages, and disadvantages for each method. Next, in Subsection 4.2, the formulations and considerations about the precision metrics used by researchers are given. Subsection 4.3 summarizes the overall discoveries of this SLR. Subsection 4.4 details answers related to each research question, as defined in Subsection 2.1. Finally, the main trends identified in the literature are presented in Subsection 4.5.

As mentioned earlier, several approaches were found for forecasting methods. One can imagine grouping the methods to examine each category in a structured manner. Owing to simplification, a distinction between parametric and non-parametric methods will be adopted; in a sense, parametric approaches rely on some form of distributional assumption (or data-generating process), whereas the latter do not (Babai et al., 2019). A more interested reader can refer to (Januschowski et al., 2020) for a more detailed discussion.

4.1. Forecasting Methods

Exponential smoothing (ES) is a well-known method widely used by many authors in literature as a benchmark and implemented in several commercial software (e.g., Forecast Pro and SAP SCM). It is a parametric approach that predicts a demand value by weighting all past values, with the weights decreasing exponentially over time as the observations get older. The most basic form of this method is the ES with a one-step-ahead (*h* = *1*) forecast, which is presented in Eq. 1:

$$\hat{y}_{t+1} = \alpha y_t + (1-\alpha)\hat{y}_{t-1} \quad (1)$$

where $\hat{y}_{t+1}$ represents a forecast for time t +1,

y_t is the demand size at time t,

and $0 \leq \alpha \leq 1$ is a smoothing parameter that controls the impact of older observations.

ES has the advantage of being quickly adjusted and does not require large historical data or many predictors (Yelland, 2010). However, it works only with time-series data. Other variants of the ES method have been applied to other demand patterns, such as trend and seasonality, by Matsumoto and Komatsu (2015), Kacmáry et al. (2019), Jiang et al. (2021), Cao et al. (2022), Chien et al. (2023).

Next, the CR method was designed to address intermittency (Croston, 1972), and it has been widely applied to this demand type. It estimates an interval between consecutive demands ($\hat{p}_t$) and the size of a demand (z_t) independently. When no demand occurs, an estimate remains unchanged; otherwise (i.e., $y_t > 0$), an estimate for a time t +1 is obtained as follows in Equations 2a and 2b, and the final forecast is calculated as in Equation 2c:

$$z_t = \alpha y_t + (1-\alpha) z_{t-1}, \text{(2a)}$$

$$\hat{p}_t = \alpha p_t + (1-\alpha)\hat{p}_{t-1}, \text{(2b)}$$

$$\hat{y}_{t+1} = \frac{z_t}{\hat{p}_t}, \text{ (2c)}$$

where p_t is the interval between consecutive demands at the time step t,
and $0 \leq \alpha \leq 1$ is a smoothing parameter (as in the ES method).

More recent implementations of the CR method consider a different smoothing parameter (β) for the interval estimate (Wallström and Segerstedt, 2010; Snyder et al., 2012; Kourentzes, 2014; Chandriah and Naraganahalli, 2021).

Croston's work was seminal in the field of intermittent demand. Its method had a strong influence on many other developments in the literature. That is the case of the approach used by Heinecke et al. (2013). The authors argued that the CR approach is positively biased and assessed a deflating factor, as in Eq. 3:

$$\hat{y}_{t+1} = \left(1 - \frac{\beta}{2}\right)\frac{z_t}{\hat{p}_t}. \text{ (3)}$$

The demand and interval are estimated in the SBA method as in the CR method. The SBA method has a negative bias, which is a disadvantage. Furthermore, a critical effect of intermittent demands is obsolescence, especially in scenarios with many items to be predicted. Babai et al. (2014) discussed a forecasting method, Teunter-Syntetos-Babai (TSB), to capture obsolescence risk in the data and to calculate a demand occurrence probability. Other studies have assessed the TSB method's performance (Pennings et al., 2017; Zhu et al., 2020; Kourentzes and Athanasopoulos, 2021).

The autoregressive integrated moving average (ARIMA) method can handle a wide range of time-series patterns, and a methodology for adjusting a model was introduced by Box et al. (2015). In general, its applications are limited to stationary time-series data, although other variants can consider seasonality (Gamberini et al., 2010) and even other variables (exogenous) (Gonçalves et al., 2021). The standard ARIMA model is given below:

$$y'_t = c + \phi_1 y'_{t-1} + \cdots + \phi_p y'_{t-p} + \Theta_1 \varepsilon_{t-1} + \cdots + \Theta_q \varepsilon_{t-q} + \varepsilon_t, \text{(4)}$$

where y'_t is the original series after d operations of differentiation (i.e., the difference between consecutive observations to make a non-stationary series stationary),

$\{\phi_1, \cdots, \phi_p\}$ are the coefficients of the autoregressive part, $\{\Theta_1, \cdots, \Theta_q\}$ are the coefficients of the moving average part of the model, $\{\varepsilon_{t-1}, \cdots, \varepsilon_{t-q}\}$ are the error terms of the moving average part of the model, and c is a constant.

The Equation (4) can be referred to as the ARIMA (p,q,d) model.

All the parametric methods described so far have the advantage of producing forecasts more rapidly than many non-parametric approaches. However, parametric methods assume specific characteristics in time-series data, such as intermittency, stationarity, obsolescence, linearity, etc. These characteristics do not hold in most cases of real-world problems. Many non-parametric methods have been applied to the spare parts forecasting problem to overcome this.

ANN is a non-parametric data-driven model inspired by biological systems, such as the human brain (Kourentzes, 2013). These models are arranged by artificial neurons (nodes) and connections (weights). In this approach, neurons receive input signals and transform them into output signals via an activation function (Zhang et al., 1998). A single-hidden layer feedforward ANN model for time-series forecasting is given as follows:

$$\hat{y}_{t+1} = \sum_{i=1}^{n} \beta_i g(w_i^T x_t + b_i) \quad (5)$$

where N is the number of hidden neurons,

$\boldsymbol{\beta}_i = (\beta_{i1}, \beta_{i2}, \ldots, \beta_{im})^T$ is the weight vector connecting the hidden neurons to the output vector,

$\mathbf{w}_i = (w_{i1}, w_{i1}, \ldots, w_{in})^T$ is the weight vector which connects the input vector to the i-th hidden neuron,

b_i is the bias associated with the i-th hidden neuron, $g(.)$ is an activation function,

and $\boldsymbol{x}_t = (x_{t1}, x_{t2}, \ldots, x_{tn})^T \in R^n$ is the input vector associated with time t using n variables.

It should be pointed out that the input vector x_t usually is used to model a relationship between the demand variable (target) y_t and its lagged values $(y_{t-1}, y_{t-2}, \ldots, y_{t-n})$ as in an autoregression model.

Further, some studies have assessed the use of time-series-based features in ANNs. For example, Lolli et al. (2017) evaluate the use of demand value, the number of periods separating the last non-zero demand, and the "cumulative successive periods with zero demands" as input to an ANN-based model. Other applications of neural networks can be found in (Chen et al., 2010; Dombi et al., 2018; Liu et al., 2019; Li et al., 2020; Zhang et al., 2023).

Lastly, random forest (RF) based methods were also found during the review. RF was originally proposed by Breiman (2001) and consists of a combination of forecasts from a set of randomly generated decision trees. An RF model can be described as a set of R trees $\{T_1(x_t), T_2(x_t), \ldots, T_R(x_t)\}$ which generate R individual forecasts, i.e., $\{\hat{y}_1 = T_1(x_t), \hat{y}_2 = T_2(x_t), \ldots, \hat{y}_R = T_R(x_t)\}$ with $\hat{y}_i$ ($i = 1,2,\ldots,R$) being the prediction associated with the i-th decision tree. The main objective of the RF is to generate a set of uncorrelated decision trees, each of which grows using bootstrap sampling of the training set. For example, the mean time between failures (and spare parts demand) was forecasted in the study by Choi and Suh (2020) using RF, achieving good accuracy. Other works can be found in (Steenbergen and Mes, 2020; Hao et al., 2023; Hong et al., 2023).

Although the mentioned non-parametric approaches do not require specific analysis to gain insights into the underlying data generating processes, they are commonly known as "data-hungry" methods (requiring large amounts of data). They might require intensive calculation operations, which can be viewed as a disadvantage.

4.2. Evaluation Metrics

According to SLR results, many precision metrics have been used to evaluate the predictive performance of the methods. Some of them have a direct interpretation, as in the case of the mean error (ME), where the focus is on verifying the presence of bias. At the same time, others are built based on the scale of output changes to enable comparisons between different datasets. That is the case of mean absolute scaled error (MASE).

According to the literature, root mean squared error (RMSE) is the most applied metric. RMSE is generally used to evaluate approaches to regression problems that are still outside the spare parts context. Nonetheless, RMSE is more sensitive to outliers in the data. The same applies to mean squared error (MSE), with the difference that it is commonly used to optimize the parameters of the proposed methods or benchmark models (Kourentzes, 2014). To overcome this disadvantage, some authors argued in favor of using mean absolute error (MAE), which is also used to fit the parameters of the specific methods (Kourentzes, 2014).

Mean absolute percentage error (MAPE) has been used to evaluate many new methods because of its relatively simple interpretation. However, MAPE can cause numerical problems (undefined or infinity) due to the possibility of division by zero. For example, one can use the MAE because it does not use the original time-series values in the denominator. Table 3 presents the formulations for the accuracy metrics described. H notation is used to express the test set size, in other words, the number of predictions required after time t, and k is used to index over the training set (with n samples), y_i and $\hat{y}_i$ are the true and predicted values at time step i, respectively.

Table 3

Equations for accuracy measurements.

Evaluation metric	**Equation**
RMSE	$\sqrt{\frac{1}{H}\sum_{i=1}^{H}}$
MAPE	$\frac{1}{H}\sum_{i=1}^{H} 100y_{i-\hat{y}_i \vee \overline{y_{i-}}}$
MSE	$\frac{1}{H}\sum_{i=1}^{H}$
ME	$\frac{1}{H}\sum_{i=1}^{H}$
MAE	$\frac{1}{H}\sum_{i=1}^{H} y_{i-\hat{y}_i \vee}$
MASE	$\frac{1}{H}\lfloor \frac{y_{i-\hat{y}_i}}{\frac{1}{n-1}\sum_{k=2}^{n} y_k - y_{k-1} \vee}$

4.3. Overall Results

The selected papers are presented in Table 4, where column “Reference” is the paper reference, column “Journal Title” is the title of the journal; column “Industry” indicates the branch (or branches) of the application (RQ_1); column “Model” specifies the employed forecasting method(s) (RQ_2), where P indicates a parametric model and NP a non-parametric model; column “Demand Type” is the demand characteristics; and column “Citation Number” is the number of citations of the paper. RQ_3 was the subject of Table 2 discussed in Subsection 4.2.

It should be noted that the main extraction fields were present in most of the selected papers. In the industry type (RQ_1) cases, only 6.0% of cases were not reported by the authors. Regarding question RQ_2, 57, 39, and 32 studies used parametric, non-parametric, and both approaches, respectively. Regarding demand type (RQ_4), a representative proportion (81.0%) of studies reported the specific characteristics in the data. Thus, a suitable database was built to proceed with the investigation.

4.4. Research Questions Findings

Regarding RQ_1, the two main branches subject to forecasting applications are automotive and aircraft. Other branches can be further exploited due to their importance to society, as in military areas (7.9% of cases). An essential aspect of RQ_2 must be highlighted: only half of the works considered both approaches (parametric and non-parametric). This may open up possibilities for future research questions, such as: Which method performs better, and under what conditions?

Additionally, most of the literature uses standard metrics to evaluate the proposed approaches, such as RMSE and MAPE, which are the subject of RQ_3. Other accuracy measures are being proposed and used. However, it is essential to highlight a secondary evaluation criterion used by some researchers: inventory control evaluation metrics, such as customer service or inventory costs. This is a good practice for forecasting applications and an extension of the analysis of their impact. Therefore, it is an aspect recommended for new researchers.

The responses for RQ_4 reveal a strong presence of intermittent items. However, other demand patterns were identified in this SLR, including seasonal, stationary, and other. The proposal of specific parametric or non-parametric methods for forecasting intermittent demand can cover a broader range of industries, thereby amplifying its impact in the spare parts industry, such as automotive and aircraft.

4.5. Research trends

Research trends in a given field are crucial for understanding the latest advances and gaps, and for aligning new research with emerging needs. In addition, understanding trends helps formulate hypotheses and direct research toward areas with the greatest potential for academic and practical impact. In that sense, Figure 7 shows the trend in the types of models used for forecasting applications in industry between 2010 and 2023.

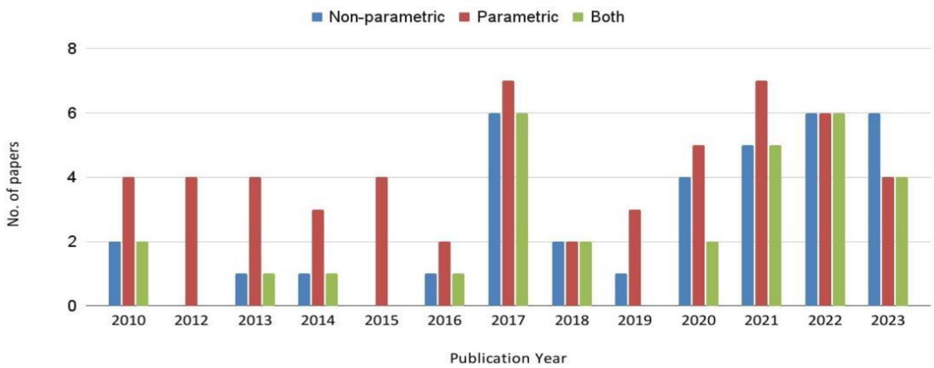

Figure 7: Model types distribution along years.

It should be noted that the number of studies using non-parametric approaches is increasing. Furthermore, the application of both approaches increases, which can be related to the increase in non-parametric approaches. For example, the same study used both parametric and non-parametric methods, i.e., methods that do not make assumptions about the data-generating process. This is an interesting finding, since developing both models together can improve overall performance by employing strategies based on combinations (Cao et al., 2022) or stacking (Tsao et al., 2024). Additionally, there is a trend related to the data characteristics reported in the literature. Figure 8 presents the distribution of data types according to the information reported by authors.

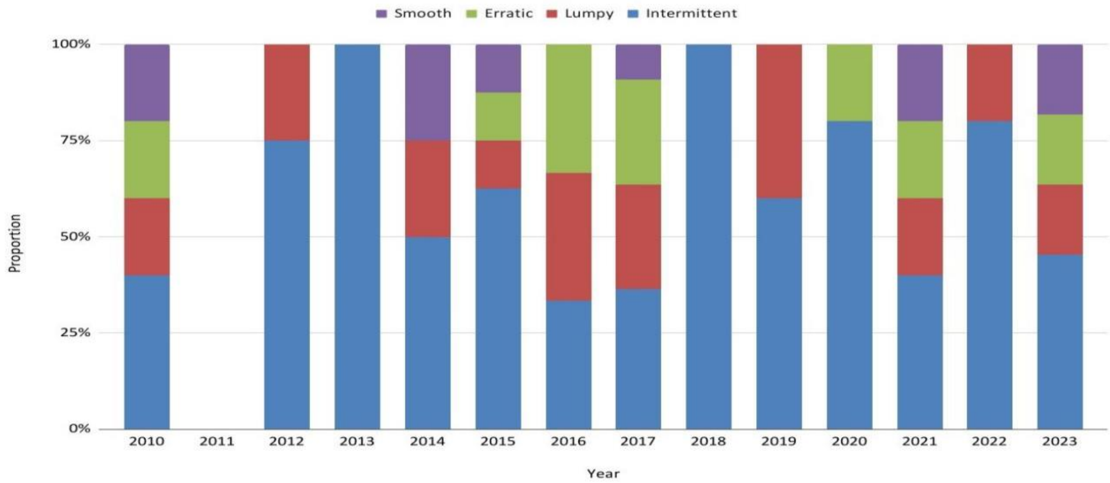

Figure 8: Data types reported distribution.

According to Figure 8, intermittent and lumpy types are predominant over time. This trend reinforces statements made by some authors (Babai et al., 2014) that some segments are more affected by intermittency, and that these branches are at the top of the list reported in the literature, according to the results of this SLR (presented in subsection 3.5). In other words, new methods focusing on these data types have significant potential impact. Besides, it is possible to link the increase in the use of non-parametric methods to these types of data, since applying parametric models combined with non-parametric methods can improve forecasting performance for these items. This is mainly because non-parametric approaches can learn and extract these patterns from data using other predictors as inputs (Zhang et al., 2023; Caserta and D'Angelo, 2024). In summary, intermittent items are predominant in most branches of the literature. Furthermore, there has been an increasing trend of applying non-parametric approaches (e.g., ANN) in recent years.

5. Conclusion and recommendations

In this study, a Systematic Literature Review was conducted to present an overview of the state of-the-art in forecasting approaches for industrial applications focused on spare parts, using real-world problem data. The applied methodology has considered many databases to reach most of the developments.

The results reveal a dominance of two specific industrial branches over the others: automotive and aircraft. This can be partially motivated by the challenges decision-makers face when managing spare parts: the variability of inter-demand intervals and demand size variance. Thus, most of the methods developed are focused on intermittent patterns.

Most parametric approaches have been developed by evolving the ideas introduced by Croston (1972), which treats the interval between demands and the demand size as separate variables. On the other hand, non-parametric approaches have been applied to the same problem and have gained the attention of the academic community. The results of this SLR can be helpful to new scholars studying demand forecasting problems, as it provides a theoretical background and standard practices.

Regarding future research directions, new approaches should evaluate methodologies that account for the full life cycles of spare parts, since managerial decisions should be taken throughout the life cycle. Just 3% of the works adopt this point of view. Another direction is to evaluate inventory models, which makes sense from a practical point of view. A considerable number of papers (39.6%) conducted some form of inventory control evaluation, but there is room for improvement.

Finally, using explanatory variables and forecasting combinations (Petropoulos and Kourentzes, 2015) can be a potential strategy to improve forecasting performance, as it leverages multiple sources of prediction, such as stacking designs. Furthermore, the performance of models using explanatory variables can be improved by leveraging data generated in industrial process digitization initiatives (Choi and Suh, 2020). Using explanatory variables can improve forecasting performance by enabling the model to learn and anticipate changes from external features beyond the time-series data.

Table 4
Selected papers for this review.

Reference	Journal Title	Industry	Model	Demand type	Citation Number
(Kourentzes, 2013)	International Journal of Production Economics	Automotive	P, NP	Intermittent	127
(Petropoulos and Kourentzes, 2015)	Journal of The Operational Research Society	Aircraft	P	Intermittent	77
(Lolli et al., 2017)	International Journal of Production Economics	Automotive	P, NP	Intermittent, Lumpy, Erratic, Smooth	76
(Snyder et al., 2012)	International Journal of Forecasting	Automotive	P	Intermittent	69
(Wallström and Segerstedt, 2010)	International Journal of Production Economics	-	P	Intermittent, Lumpy, Erratic, Smooth	61
(Romeijnders et al., 2012)	European Journal of Operational Research	Aircraft	P	Intermittent, Lumpy	57
(Kourentzes, 2014)	International Journal of Production Economics	Automotive	P	Intermittent	48
(Chandriah and Naraganahalli, 2021)	Multimedia Tools and Applications	Automotive	P, NP	Intermittent	43
(Kim et al., 2017)	Computers and Industrial Engineering	Refrigerator	P	Erratic	42
(Babai et al., 2014)	International Journal of Production Economics	Automotive, Military	P	Lumpiness, Smooth	40
(Babai et al., 2019)	International Journal of Production Economics	Military, Automotive	P	Intermittent, Lumpy	39
(Kück and Freitag, 2021)	International Journal of Production Economics	-	P, NP	Non-Intermittent, Regular	38
(Moon et al., 2012)	International Journal of Production Economics	Navy	P	Intermittent	38
(Nikolopoulos et al., 2016)	International Journal of Production Economics	Automotive	P, NP	Intermittent	35
(Matsumoto and Komatsu, 2015)	The International Journal of Advanced Manufacturing Technology	Automotive	P	Seasonal	34
(Matsumoto and Ikeda, 2015)	Journal of Remanufacturing	Automotive	P	Seasonal	33
(Yelland, 2010)	International Journal of Forecasting	Semiconductor	P, NP	-	32
(Steenbergen and Mês, 2020)	Decision Support Systems	Agricultural	NP	-	31

(Petropoulos et al., 2016)	International Journal of Production Economics	Aircraft, Automotive	P	Erratic, Lumpy	30
(Zhu et al., 2020)	Reliability Engineering and System Safety	Aircraft, Railway	P	Intermittent	28
(Gonçalves et al., 2021)	Decision Support Systems	Automotive	P, NP	Seasonal, Non-Stationary	25
(Babai et al., 2020)	IMA Journal of Management Mathematics	Aircraft	P, NP	Intermittent	23
(Guo et al., 2017)	Computers & Industrial Engineering	Aircraft	P, NP	-	22
(Tracht et al., 2013)	CIRP Annals - Manufacturing Technology	Energy	P	-	22
(Kourentzes and Athanasopoulos, 2021)	European Journal of Operational Research	Aircraft	P	Intermittent	21
(Gamberini et al., 2010)	Mathematical Problems in Engineering	Hydraulic	P	Sporadic, Irregular, Trend, Seasonal	21
(Jiang et al., 2021)	International Journal of Production Research	Heavy-duty vehicle	P, NP	Slow, Erratic, Lumpy, Smooth, Intermittent	20
(Moon et al., 2013)	International Journal of Production Economics	Military	P	Intermittent	20
(Dombi et al., 2018)	International Journal of Production Economics	Semiconductor	P, NP	-	19
(Pennings et al., 2017)	European Journal of Operational Research	Lamp, Semiconductor, Military, Automotive	P, NP	Intermittent	19
(Chen et al., 2010)	Expert Systems with Applications	Semiconductor	P, NP	-	17
(Heinecke et al., 2013)	International Journal of Production Economics	Automotive, Military, Semiconductor	P	Intermittent	16
(Rosienkiewicz et al., 2017)	Applied Mathematical Modelling	Mining	P, NP	Lumpy	15
(Bergman et al., 2017)	Robotics and Computer-Integrated Manufacturing	-	P, NP	Intermittent	13
(Zhuang et al., 2022)	Data Science and Management	Automotive	P, NP	Intermittent, Lumpy	12
(Vargas and Cortés, 2017)	International Journal of Automotive and Mechanical Engineering	Automotive	P, NP	Erratic, No Intermittent	11
(Choi and Suh, 2020)	Sustainability	Aircraft	P, NP	Intermittent, Slow-Moving, Erratic	10

(Liu et al., 2019)	IEEE Transactions on Fuzzy Systems	Automotive	NP	-	8
(Li et al., 2020)	International Journal of Production Research	Military	NP	Intermittent	7
(Vaitkus et al., 2014)	Elektronika ir Elektrotechnika	Electrical	P, NP	-	5
(Alalawin et al., 2020)	Journal of Quality in Maintenance Engineering	Automotive	P	-	4
(Kim et al., 2023)	Mathematics	Aircraft	P, NP	-	3
(Sareminia, 2022)	Neural Processing Letters	Steel	P, NP	Chaotic	3
(Kaˇcmáry et al., 2019)	Management Systems in Production Engineering	Automotive	P	-	3
(Vasumathi and Saradha, 2015)	Indian Journal of Science and Technology	Steel, Iron	P	Intermittent	3
(Guimaraes et al., 2020)	South African Journal of Industrial Engineering	Agricultural, Construction	P	High-Turnover, Medium-Turnover, Low-Turnover, Very-Low-Turnover, Seasonal	2
(Sareminia and Amini, 2023)	Computers in Industry	Steel	NP	Low-Demand, Intermittent, Irregular	1
(Zhang et al., 2023)	Annals of Operations Research	Aircraft	P, NP	Intermittent, Lumpy, Smooth, Erratic	1
(Lee et al., 2022)	Sustainability (Switzerland)	Military	P, NP	Intermittent	1
(Yang et al., 2022)	Scientific Programming	Aircraft	P, NP	-	1
(Faghidian et al., 2021)	Journal of Engineering Research	Automotive	P, NP	Intermittent, Lumpy, Smooth, Erratic	1
(Chien et al., 2023)	Computers & Industrial Engineering	Automotive	P, NP	Intermittent, Lumpy, Smooth, Erratic	0
(Hao et al., 2023)	International Journal of Innovative Computing, Information and Control	Power Equipment	NP	Intermittent	0
(Hong et al., 2023)	Sensors	Engineering Manufacturing	P, NP	Intermittent	0
(Cao et al., 2022)	South African Journal of Industrial Engineering	Aircraft	P, NP	Intermittent	0
(Hoffmann et al., 2022)	Logistics Research	Mechanical Engineering	P, NP	Intermittent	0
(O'Neal et al., 2021)	Journal of Defense Analytics and Logistics	Aircraft	P	-	0

(Saravanan et al., 2019)	International Journal of Recent Technology and Engineering	Compressor	P	Stationary	0
(Bounou et al., 2018)	International Journal of Supply Chain Management	-	P, NP	Intermittent	0
(Bing et al., 2012)	Modern Applied Science	Steel	P	-	0
(Affonso et al., 2024)	Decision Analytics Journal	Mining	P, NP	Intermittent, Erratic, Regular, Irregular	0
(Tsao et al., 2024)	International Journal of Industrial Engineering: Theory Applications and Practice	Natural Gas	P, NP	Lumpy, Smooth, Erratic	0
(Caserta and D'Angelo, 2024)	Journal of the Operational Research Society	Electric	NP	Intermittent, Lumpy, Erratic	0

References

Affonso, T. B., Conceição, S. V., Muniz, L. R., De Freitas Almeida, J. F. and De Lima, J. C. (2024). A new hybrid forecasting method for spare part inventory management using heuristics and bootstrapping', Decision Analytics Journal 10, 100415.

Alalawin, A., Arabiyat, L. M., Alalaween, W., Qamar, A. and Mukattash, A. (2020). Forecasting vehicle's spare parts price and demand. Journal of Quality in Maintenance Engineering 27(3), 483 – 499. Publisher: Emerald Group Holdings Ltd. Type: Article.

Babai, M. Z., Dallery, Y., Boubaker, S. and Kalai, R. (2019). A new method to forecast intermittent demand in the presence of inventory obsolescence. International Journal of Production Economics 209, 30–41.

Babai, M. Z., Syntetos, A. and Teunter, R. (2014). Intermittent demand forecasting: an empirical study on accuracy and the risk of obsolescence. International Journal of Production Economics 157, 212–219.

Babai, M. Z., Tsadiras, A. and Papadopoulos, C. (2020). On the empirical performance of some new neural network methods for forecasting intermittent demand. IMA Journal of Management Mathematics 31(3), 281 – 305. Publisher: Oxford University Press.

Bacchetti, A. and Saccani, N. (2012). Spare parts classification and demand forecasting for stock control: investigating the gap between research and practice. Omega 40(6), 722– 737.

Bergman,J.J., Noble,J.S., McGarvey, R.G. and Bradley, R.L. (2017). A Bayesian approach to demand forecasting for new equipment programs. Robotics and Computer-Integrated Manufacturing 47, 17–21.

Bing, C., Shouqun, S. and Gang, L. (2012). An optimized unbiased GM (1, 1) power model for forecasting MRO spare parts inventory. Modern Applied Science 6(6), 12 – 17.

Bounou, O., El Barkany, A. and El Biyaali, A. (2017). Inventory models for spare parts management: a review. International Journal of Engineering Research in Africa 28, 182–198.

Bounou, O., El Barkany, A. and El Biyaali, A. (2018). Parametric approaches for spare parts demand. International Journal of Supply Chain Management. 7(4), 432 – 439. Publisher: ExcelingTech.

Box, G., Jenkins, G., Reinsel, G. and Ljung, G. (2015). Time series analysis: forecasting and control. Wiley Series in Probability and Statistics, Wiley.

Breiman, L. (2001). Random forests. Machine Learning 45(1), 5–32.

Cao,Y., Liu,Y. and Shen, D. (2022). Methods for forecasting demand in repairing an airline's repairable line replaceable unit parts. South African Journal of Industrial Engineering 33(4), 60–80.

Caserta, M. and D. Angelo, L. (2024). Intermittent demand forecasting for spare parts with little historical information. pp. 1–16.

Chandriah, K. K. and Naraganahalli, R. V. (2021). RNN / LSTM with modified Adam optimizer in deep learning approach for automobile spare parts demand forecasting. Multimedia Tools and Applications 80(17), 26145 – 26159. Publisher: Springer.

Chen, F.-L., Chen, Y.-C. and Kuo, J.-Y. (2010). Applying moving back-propagation neural network and moving fuzzy neuron network to predict the requirement of critical spare parts. Expert Systems with Applications 37(6), 4358 – 4367.

Chien, C.-F., Ku, C.-C. and Lu, Y.-Y. (2023). Ensemble learning for demand forecast of After-Market spare parts to empower data-driven value chain and an empirical study. Computers & Industrial Engineering 185, 109670.

Choi, B. and Suh, J. H. (2020). Forecasting spare parts demand of military aircraft: comparisons of data mining techniques and managerial features from the case of south korea. Sustainability.

Chow, W. S. and Chan, L. S. (2008). Social network, social trust and shared goals in organizational knowledge sharing. Information & Management, 45(7), 458-465.

Croston, J. D. (1972). Forecasting and stock control for intermittent demands. Journal of the Operational Research Society 23, 289–303.

Dombi, J., Jónás, T. and Tóth, Z. E. (2018). Modelling and long-term forecasting demand in spare parts logistics businesses. International Journal of Production Economics 201, 1– 17.

Faghidian, S. F., Khashei, M. and Khalilzadeh, M. (2021). Improving intermittent demand forecasting based on data structure. Journal Of Engineering Research.

Frank, A. G., Dalenogare, L. S. and Ayala, N. F. (2019). Industry 4.0 technologies: implementation patterns in manufacturing companies. International Journal of Production Economics 210, 15–26.

Gamberini,R., Lolli,F., Rimini,B. and Sgarbossa, F. (2010). Forecasting of sporadic demand patterns with seasonality and trend components: an empirical comparison between Holt Winters and (S)ARIMA methods. Mathematical Problems in Engineering.

Gonçalves, J. N. C., Cortez, P., Carvalho, M. S. and Frazão, N. M. (2021). A multivariate approach for multi-step demand forecasting in assembly industries: empirical evidence from an automotive supply chain. Decision Support Systems 142, 113452.

Guimaraes, C., Marques, J. and Tortato, U. (2020). Demand forecasting for high-turnover spare parts in agricultural and construction machines: a case study. South African Journal of

Industrial Engineering 31(2),116–128. Publisher: South African Institute of Industrial Engineering.

Guo, F., Diao, J., Zhao, Q., Wang, D. and Sun, Q. (2017). A double-level combination approach for demand forecasting of repairable airplane spare parts based on turnover data. Computers & Industrial Engineering 110, 92–108.

Hao, Y., Tian, M., Wang, Y. and Huang, M. (2023). Demand forecasting for rush repair spare parts of power equipment using fuzzy c-means clustering and the fuzzy decision tree.

Hasni, M., Aguir, M., Babai, M. and Jemai, Z. (2019). Spare parts demand forecasting: a review on bootstrapping methods. International Journal of Production Research 57(1516), 4791–4804.

Heinecke, G., Syntetos, A. A. and Wang, W. (2013). Forecasting-based SKU classification. International Journal of Production Economics 143(2), 455–462.

Hoffmann, M., Lasch, R. and Meinig, J. (2022). Forecasting irregular demand using single hidden layer neural networks. Logistics Research. Publisher: Bundesvereinigung Logistik (BVL).

Hong, K., Ren, Y., Li, F., Mao, W. and Gao, X. (2023). Robust interval prediction of intermittent demand for spare parts based on tensor optimization. Sensors 23(16), 7182.

Januschowski, T., Gasthaus, J., Wang, Y., Salinas, D., Flunkert, V., Bohlke-Schneider, M. and Callot, L. (2020). Criteria for classifying forecasting methods. International Journal of Forecasting 36(1), 167–177.

Jiang, P., Huang, Y. and Liu, X. (2021). Intermittent demand forecasting for spare parts in the heavy-duty vehicle industry: a support vector machine model. International Journal of Production Research 59(24), 7423 – 7440. Publisher: Taylor and Francis Ltd.

Kacmáry, P., Malindžák, D. and Spišák, J. (2019). The design of forecasting system used for prediction of electro-motion spare parts demands as an improving tool for an enterprise management. Management Systems in Production Engineering 27(4), 242 – 249. Publisher: Sciendo.

Kim, J.-D., Kim, T.-H. and Han, S. W. (2023). Demand forecasting of spare parts using artificial intelligence: a case study of K-X tanks. Mathematics. Publisher: MDPI.

Kim, T. Y., Dekker, R. and Heij, C. (2017). Spare part demand forecasting for consumer goods using installed base information. Computers and Industrial Engineering 103, 201 – 215. Publisher: Elsevier Ltd.

Kitchenham, B. A. (2012). Systematic review in software engineering: where we are and where we should be going. Proceedings of the 2nd international workshop on evidential assessment of software technologies. ACM, Lund Sweden, pp. 1–2.

Kourentzes, N. (2013). Intermittent demand forecasts with neural networks. International Journal of Production Economics 143(1), 198–206.

Kourentzes, N. (2014). On intermittent demand model optimisation and selection. International Journal of Production Economics 156, 180–190.

Kourentzes, N. and Athanasopoulos, G. (2021). Elucidate structure in intermittent demand series. European Journal of Operational Research 288(1), 141 – 152. Publisher: Elsevier B.V.

Kulshrestha, N., Agrawal, S. and Shree, D. (2024). Spare parts management in industry 4.0 era: a literature review. Journal of Quality in Maintenance Engineering.

Kück, M. and Freitag, M. (2021). Forecasting of customer demands for production planning by local k-nearest neighbor models. International Journal of Production Economics 231, 107837.

Lee, E., Nam, M. and Lee, H. (2022). Tab2vox: CNN-based multivariate multilevel demand forecasting framework by tabular-to-voxel image conversion. Sustainability (Switzerland). Publisher: MDPI.

Li, X., Zhao, X. and Pu, W. (2020). Battle damage-oriented spare parts forecasting method based on wartime influencing factors analysis and ε-support vector regression. International Journal of Production Research 58(4), 1178 – 1198. Publisher: Taylor and Francis Ltd.

Liu, Y., Zhang, Q., Fan, Z.-P., You, T.-H. and Wang, L.-X. (2019). Maintenance spare parts demand forecasting for automobile 4S shop considering weather data. IEEE Transactions On Fuzzy Systems 27(5, SI), 943–955.

Lolli, F., Gamberini, R., Regattieri, A., Balugani, E., Gatos, T. and Gucci, S. (2017). Single hidden layer neural networks for forecasting intermittent demand. International Journal of Production Economics 183, 116–128.

Matsumoto, M. and Ikeda, A. (2015). Examination of demand forecasting by time series analysis for auto parts remanufacturing. Journal of Remanufacturing 5(1), 1.

Matsumoto, M. and Komatsu, S. (2015). Demand forecasting for production planning in remanufacturing. The International Journal of Advanced Manufacturing Technology 79(1-4), 161–175.

Moon, S., Hicks, C. and Simpson, A. (2012). The development of a hierarchical forecasting method for predicting spare parts demand in the South Korean Navy-A case study. International Journal of Production Economics 140(2), 794–802.

Moon, S., Simpson, A. and Hicks, C. (2013). The development of a classification model for predicting the performance of forecasting methods for naval spare parts demand. International Journal of Production Economics 143(2), 449–454.

Nikolopoulos, K. I., Babai, M. Z. and Bozos, K. (2016). Forecasting supply chain sporadic demand with nearest neighbor approaches. International Journal of Production Economics 177, 139–148.

O.Neal, T. R., Dickens, J. M., Champagne, L. E., Glassburner, A. V., Anderson, J. R. and Breitbach, T. W. (2021). Sortie-based aircraft component demand rate to predict requirements. Journal of Defense Analytics and Logistics 5(2), 214 – 223. Publisher: Emerald Publishing.

Pennings, C. L., van Dalen, J. and van der Laan, E. A. (2017). Exploiting elapsed time for managing intermittent demand for spare parts. European Journal of Operational Research 258(3), 958 – 969. Publisher: Elsevier B.V.

Peroni, S. and Shotton, D. (2020). OpenCitations, an infrastructure organization for open scholarship. Quantitative Science Studies 1(1), 428–444.

Petropoulos, F. and Kourentzes, N. (2015). Forecast combinations for intermittent demand. Journal Of The Operational Research Society 66(6), 914–924.

Petropoulos, F., Kourentzes, N. and Nikolopoulos, K. (2016). Another look at estimators for intermittent demand. International Journal of Production Economics 181, 154–161.

Pinçe, C., Turrini, L. and Meissner, J. (2021). Intermittent demand forecasting for spare parts: a critical review. Omega 105, 102513.

Rego, J. R. and Mesquita, M. A. (2015). Demand forecasting and inventory control: a simulation study on automotive spare parts. International Journal of Production Economics 161, 1–16.

Romeijnders, W., Teunter, R. and Van Jaarsveld, W. (2012). A two-step method for forecasting spare parts demand using information on component repairs. European Journal of Operational Research 220(2), 386–393. Publisher: Elsevier B. V.

Rosienkiewicz, M., Chlebus, E. and Detyna, J. (2017). A hybrid spares demand forecasting method dedicated to mining industry. Applied Mathematical Modelling 49, 87 – 107. Publisher: Elsevier Inc.

Saravanan, A., Anbuudayasankar, S., Arul William David, P. and Narassima, M. (2019). Forecasting techniques for sales of spare parts. International Journal of Recent Technology and Engineering 8(3), 27 – 30. Publisher: Blue Eyes Intelligence Engineering and Sciences Publication.

Sareminia, S. (2022). A support vector based hybrid forecasting model for chaotic time series: spare part consumption prediction. Neural Processing Letters. Early Access.

Sareminia, S. and Amini, F. (2023). A reliable and ensemble forecasting model for slow moving and repairable spare parts: data mining approach. Computers in Industry 145, 103827.

Snyder, R. D., Ord, J. K. and Beaumont, A. (2012). Forecasting the intermittent demand for slow-moving inventories: a modelling approach. International Journal of Forecasting 28(2), 485–496.

Steenbergen, R. M. v. and Mes, M. R. K. (2020). Forecasting demand profiles of new products. Decision Support Systems 139, 113401.

Syntetos, A. A., Boylan, J. E. and Croston, J. D. (2005). On the categorization of demand patterns. Journal of the Operational Research Society 56(5), 495–503.

Tracht, K., Goch, G., Schuh, P., Sorg, M. and Westerkamp, J. F. (2013). Failure probability prediction based on condition monitoring data of wind energy systems for spare parts supply. CIRP Annals - Manufacturing Technology 62(1), 127 – 130.

Tranfield, D., Denyer, D. and Smart, P. (2003). Towards a methodology for developing evidence-informed management knowledge by means of systematic review. 14(3), 207– 222.

Tsao, Y.-C., Yaqin, A., Lu, J.-C., Kurniati, N. and Pujawan, N. (2024). Intelligent demand forecasting approaches for spare parts in the energy industry.

Vaitkus, V., Zylius, G. and Maskeliunas, R. (2014). Electrical spare parts demand forecasting. Elektronika ir Elektrotechnika 20(10), 7 – 10. Publisher: Kauno Technologijos Universitetas.

Van Der Auweraer, S., Boute, R. N. and Syntetos, A. A. (2019). Forecasting spare part demand with installed base information: a review. International Journal of Forecasting 35(1), 181–196.

Vargas, C. G. and Cortés, M. E. (2017). Automobile spare-parts forecasting: a comparative study of time series methods. International Journal of Automotive and Mechanical Engineering 14(1), 3898 – 3912. Publisher: Universiti Malaysia Pahang.

Vasumathi, B. and Saradha, A. (2015). Enhancement of intermittent demands in forecasting for spare parts industry. Indian Journal of Science and Technology. Publisher: Indian Society for Education and Environment.

Wallström, P. and Segerstedt, A. (2010). Evaluation of forecasting error measurements and techniques for intermittent demand. International Journal of Production Economics 128(2), 625–636.

Yang, Y., Liu, W., Zeng, T., Guo, L., Qin, Y. and Wang, X. (2022). An improved stacking model for equipment spare parts demand forecasting based on scenario analysis. Scientific Programming. Publisher: Hindawi Limited.

Yelland, P. M. (2010). Bayesian forecasting of parts demand. International Journal of Forecasting 26(2), 374–396.

Zhang,G., Eddy Patuwo,B. and Y.Hu, M. (1998) .Forecasting with artificial neural networks: the state of the art. International Journal of Forecasting 14(1), 35–62.

Zhang, G. P., Xia, Y. and Xie, M. (2023). Intermittent demand forecasting with transformer neural networks. Annals of Operations Research.

Zhu, S., Jaarsveld, W. v. and Dekker, R. (2020). Spare parts inventory control based on maintenance planning. Reliability Engineering and System Safety. Publisher: Elsevier Ltd.

Zhuang, X., Yu, Y. and Chen, A. (2022). A combined forecasting method for intermittent demand using the automotive aftermarket data. Data Science and Management 5(2), 43– 56.

Zotero (2024). Zotero: Your personal research assistant. Accessed: 03.09.2024.