Journal of
Engineering Sciences
Faculty of Engineering
Assiut University
JES
مجلة
العلوم الهندسية
كلية الهندسة
جامعة أسيوط
journal homepage: http://jesaun.journals.ekb.eg

Intermittent Demand Forecasting for Spare Parts Using Artificial Neural Networks and Deep Learning: Literature Review

Received 17 May 2025; Revised 15 July 2025; Accepted 16 July 2025

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Keywords
Intermittent demand; Spare parts; Forecasting; Artificial Neural Networks; Deep Learning

Abstract: Forecasting Intermittent demand for spare parts is essential for enhancing inventory management, particularly in industries where unplanned equipment downtime and inventory holding costs are significant. Conventional forecasting methods often underperform in handling the sporadic and nonlinear nature of intermittent demand. This paper presents a focused literature review on the use of Artificial Neural Networks (ANNs) and Deep Learning (DL) techniques for forecasting intermittent demand. Unlike general reviews that survey all forecasting approaches, this study concentrates specifically on neural and learning approaches to capture nonlinear patterns. The findings demonstrate that ANN and DL-based models generally outperform classical methods in forecasting accuracy, especially under highly irregular demand. Despite the advances, the availability and quality of datasets remain a significant limitation in developing robust models. Future research directions are identified, including the need for improved feature engineering, architecture optimization, and model interpretability. This review aims to support researchers understanding the potential and challenges of neural approaches for forecasting of intermittent demand for spare parts.

1. Introduction

Effective management of spare parts is highly crucial in the industrial sectors. A spare part should be readily available at the correct quantity at the appropriate time. The primary objective of management of spare parts is to strike an optimal balance between the inventory holding costs of excess, unused spare parts and the downtime costs incurred when critical spare parts are unavailable [1]. It can be inefficient to store spare parts in large quantities due to their high inventory-holding costs [2] and their high monetary value. Demand Forecasting of spare parts helps maintain an adequate inventory level at the appropriate time [3].
The authors [4] introduced a demand pattern classification based on how frequently demand occurs and how much the demand volume varies. They categorized the demand based on two

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https://doi.org/10.21608/JESAUN.2025.386170.1518

key metrics: ADI (Average Demand Interval) and CV^2 (Squared Coefficient of Variation). They introduced four distinct demand patterns as shown in Fig. 1. Smooth demand occurs frequently with relatively consistent quantities, making it the easiest to forecast. Erratic demand also occurs regularly but exhibits significant variability in demand, posing greater forecasting challenges. Intermittent demand occurs infrequently, while the variations in demand sizes tend to be low. In contrast, lumpy demand is both infrequent and highly variable in size, making it the most complex pattern to predict. The horizontal axis represents the ADI, distinguishing between frequent (ADI<1.32) and infrequent (ADI>1.32) demand occurrences, while the vertical axis represents the CV^2, distinguishing between consistent ($CV^2<0.49$) and inconsistent ($CV^2>0.49$) demand quantities.

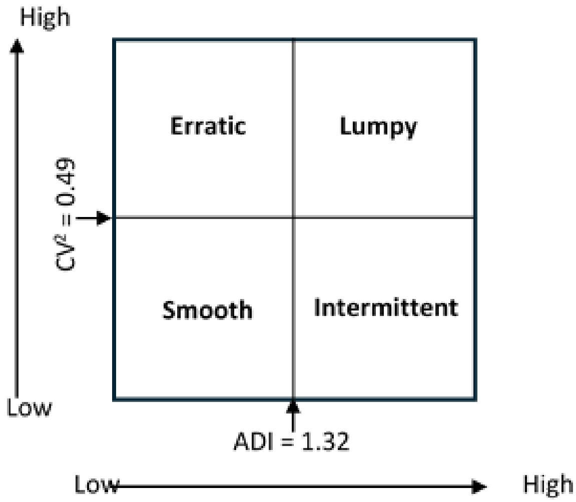

Fig. 1: Categorization of Demand

Spare parts exhibit a nature of intermittency, having long periods of zero demand [5, 6]. Intermittent demand pattern in spare parts presents a significant complexity in generating reliable forecasting [7]. There are several challenges in demand forecasting, including variability and low demand frequency. In this study, the focus is mainly on intermittent demand, as it is a common characteristic of spare parts. Due to the sporadic and irregular nature of spare parts, addressing intermittent demand is essential for developing effective forecasting models. Several methods have been employed in demand forecasting throughout the literature, including both traditional and non-traditional approaches. Conventional forecasting methods often fall short for spare parts and intermittent demand and are incapable of capturing the complexity of data patterns [8]. In such contexts, supply chains also face challenges like uncertain demand and limited resources. The study [9] provides valuable insights into using system dynamics for long-term strategic planning. Similar challenges arise in spare part management, especially with intermittent demand. In contrast, system dynamics support strategic decisions, while neural networks offer accurate, data-driven forecasting at the operational level.

Several studies provide general literature reviews that cover a broad range of forecasting methods in intermittent demand forecasting [5]. On the other hand, this paper concentrates explicitly on reviewing the literature related to intermittent demand forecasting using neural networks and deep learning. By narrowing the focus, this paper offers a more in-depth and targeted analysis of recent advancements and challenges in applying neural networks to the unique characteristics of intermittent demand. It presents a literature review on intermittent demand forecasting using neural networks and deep learning.

The objectives of this paper are investigating and categorizing peer-reviewed publications that apply neural networks to the prediction of intermittent or sporadic demand, with a particular focus on spare parts forecasting. Second, the paper seeks to analyze trends in literature by examining factors such as publication year, country of origin, application domain, and the methodologies employed. Third, it highlights the most commonly used neural network models—such as Multi-Layer Perceptron (MLP), Long Short-Term Memory networks (LSTM), and various hybrid architectures—while illustrating how artificial neural networks (ANN) have frequently been benchmarked against, and have typically outperformed, traditional forecasting techniques. Lastly, the paper identifies key research gaps in the field and proposes potential directions for future studies.

2. Neural Networks and Deep Learning

Nowadays, three leading phrases are commonly used in intelligent systems: artificial intelligence (AI), machine learning (ML), and deep learning (DL). First, AI is a comprehensive term that is used intensively. It describes the capability of machines or systems to imitate intelligent human behavior. ML, a subfield of AI, learns from data and develops models to make predictions based on training, DL is a subcategory of ML in which multilayer ANNs learn from large datasets to make more complex predictions. Fig. 2 illustrates the conceptual relationships between AI, ML, and DL. ANNs are considered the backbone of DL. The structure of the human brain inspires them. They detect patterns, make predictions, and learn from data. ANNs consist of connected nodes, known as neurons, organized into layers [10].The initial concept of neural networks was introduced in 1990 [11]. They indicated how neurons might work. Neurons serve as the fundamental processing units in a neural network. Each neuron accepts one or more inputs, then makes a computation and finally produces an output. Neurons are organized into three primary layers: the input layer, hidden layer(s), and the output layer. The input layer takes in raw data, while the hidden layers, positioned between the input and output layers, are responsible for processing the data. The architecture of an NN can vary based on the number of hidden layers included and neurons within each layer. Ultimately, the output layer delivers the result produced by the network.

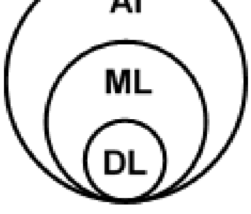

Fig. 2: AI vs ML vs DL

Through the Feedforward neural network (FNN), as its name implies, input data flows in a single forward direction. The authors in the study [12] were the first to introduce the term "Deep Neural Network (DNN)" with multiple hidden layers. The term "deep" emphasizes the depth of those layers. ANNs typically have only one hidden layer, whereas DNNs have more than one hidden layer, which can be utilized to develop more complex data patterns. ANN and DNN differ in the depth of their architecture.
In neural networks, connections between neurons have assigned weights that indicate the strength of the influence one neuron has on another. Each neuron may have an associated bias. During the training phase, the NN learns by updating these weights and biases to identify data patterns. An activation function processes the weighted sum of inputs, and a loss function evaluates the error between predicted and actual outcomes. The objective during training is to reduce this loss as much as possible. ANNs and DNNs are effective techniques for solving nonlinearities in complex problems [13]. One drawback of NN in intermittent demand applications is that they are considered 'data-hungry' models, meaning they require large datasets to train on [14].

2.1. Classification of ANN

ANNs are classified into two broad types: Feedforward Neural Networks (FNN) and Recurrent Neural Networks (RNN). Fig. **3** shows the classification of artificial neural networks.

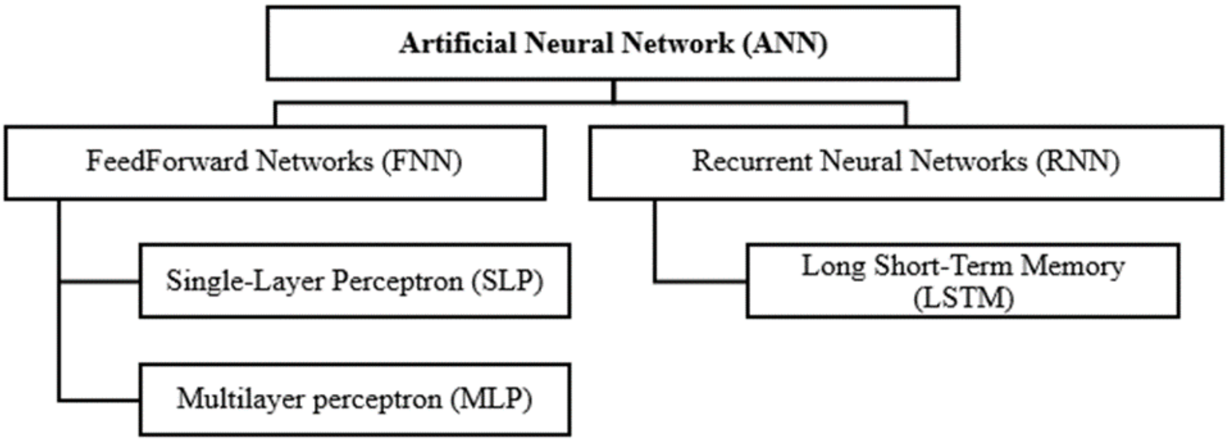

Fig. 3: Classification of ANN

2.1.1. FNN

An FNN is a kind of network where data moves through the network in a single direction. Fig. 4 illustrates the FNN Architecture. FNN can be categorized into two types of perceptrons: single-layer perceptron (SLP) and multilayer perceptrons (MLPs).

- **SLP**

An SLP is the most straightforward architecture of the FNN. It includes only one input layer connected to only one output layer.

- **MLP**

An MLP is one of the architectures of the FNN, meaning that information moves in a forward direction through the network. MLP is composed of several layers. Each layer is connected to the next layer. MLP is widely used in FFN models [8]. It is one of the most commonly and widely used NNs for forecasting. The authors [15] proposed guidelines on MLP architecture design. They suggested starting with a three-layer MLP and using the smallest number of neurons in the hidden layer. Mainly, the basic building blocks of an MLP are the input layer, the hidden layer, and the output layer. The input layer, the first layer of the network, receives the input features. The hidden layers are the intermediate layers located between the input layer and the output layer. Each node in a hidden layer is connected to every node in both the previous and subsequent layers. They are not directly observable in the input or output. The output layer produces the network's output, and the number of nodes in the output layer depends on the nature of the problem being addressed. In time series forecasting with an MLP, it is often treated as a regression problem. In the regression problem, the output is a continuous value, and the primary objective is to minimize the difference between the actual and predicted values. MLP models can be described as FNNs because the signal from one neuron to other flows only in one direction: from the input layer to the output layer.

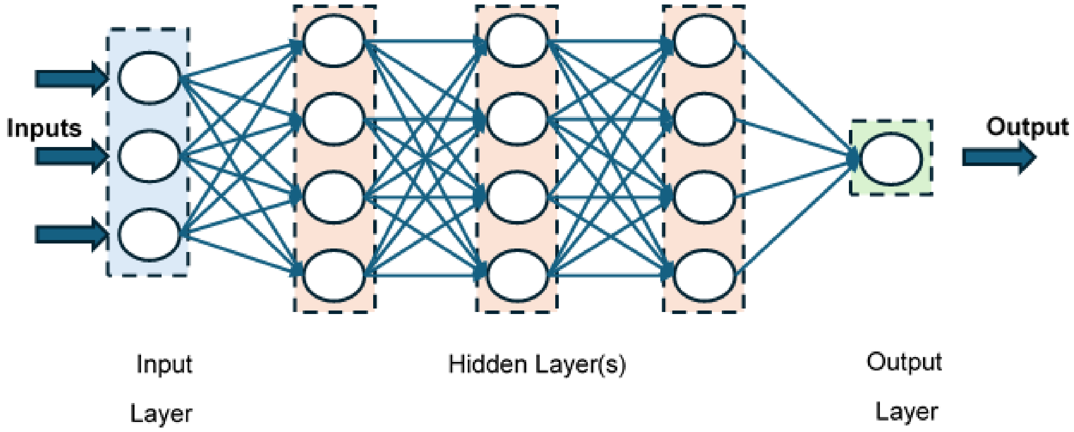

Fig. 4: FFN

The neural network is trained to learn relationships and patterns within the historical time series data, enabling it to make accurate predictions for future time steps. Backpropagation (BP), Learning Machines, Regularized loss (RL), and Levenberg–Marquardt (LM) are commonly used learning algorithms. Backpropagation (BP) is a widely used algorithm during training. It calculates the error between the actual and the predicted output and then propagates this error through a backward method. The authors [16] were the first to adopt a multilayer perceptron (MLP) for demand forecasting, utilizing the backpropagation (BP) algorithm for training. Subsequently, extreme learning machines (ELMs) were proposed as an alternative to traditional learning algorithm. In the study [17], ELMs were applied to intermittent demand forecasting, and a comparative evaluation of the BP and ELM training methods was conducted. The results [17] showed that ELM had lower computational complexity and good generalization ability. It is a fast algorithm; it determines the optimal weights in a single computational iteration. The neural networks are data-hungry [14]. To overcome this problem, the Bayesian regularization backpropagation algorithm (BRBP) [18] is used to eliminate the need for a validation dataset [19]. This algorithm has been used [14, 19] in intermittent demand forecasting. RL and LM training algorithms enable network training with small samples [14].

2.1.2. RNN

An RNN is a type of NN structure. The connections between neurons in an RNN form a cycle through feedback loops; signals flow in different directions, unlike the FNN, which moves in only one direction. The feedback loop uses sequential input values to make predictions. RNNs excel at processing sequence data for accurate predictions. An RNN has a feedback loop that allows it to pass previous information forward. It enables the hidden state to flow from one step to the next. This information is encoded in the hidden state, which acts as a representation of previous inputs. RNN is a type of ANN that can handle sequential data. Unlike MLP, each RNN receives feedback not only from the preceding layer but also from its output at the previous time. This structure enables RNNs to retain short-term memory by storing activations across consecutive time steps. Therefore, it is suitable for processing sequential data. An RNN can receive a sequence of inputs and produce a corresponding sequence of outputs [20].

- **LSTM**

A limitation of RNN is the exploding and vanishing gradient problem, making it challenging to train [20]. The best act to address this limitation is to use a gated LSTM network. Because of its storage capacity and ability to manage sequential data, it is particularly effective for time series forecasting [21]. Its architecture is typically composed of an input gate, a forget gate, a remember gate, and an output gate.

3. Research Methodology

Given the significance of the topic addressed, there is a clear need to investigate this domain further and analyze it in more detail. The review process adopted in this study is outlined in Fig. 5 and follows a systematic literature review methodology, which includes the steps shown below:

- A comprehensive online search was conducted across reputable academic databases, including Elsevier, ScienceDirect, Springer, Scopus, ResearchGate, and the Egyptian Knowledge Bank (EKB).
- The search was guided by targeted keywords including “intermittent demand, “demand forecasting”, “spare parts”, “neural networks”, and “deep learning”.
- Only articles published in the English language are considered.

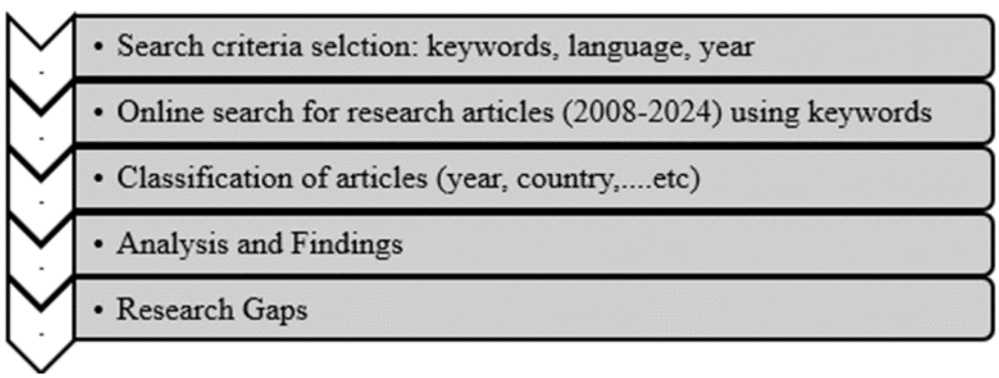

Fig. 5: Literature Review Methodology

4. Analysis of Articles

4.1. Descriptive Analysis

According to the selection criteria and keywords adopted in this study (e.g., "intermittent demand", "spare parts", etc.), a total of around 30 peer-reviewed articles published between 2008 and 2024 were identified and reviewed. The articles were classified based on the following key dimensions:

4.1.1. Year of Publication

Fig. 6 presents the distribution of publications across four time periods: before 2010, 2010-2015, 2016-2020, and 2021-2024. The data reveals a clear upward trend in research activity devoted to this area. While only four papers were published before 2010 (13%), the volume increased significantly in the most recent period, with 15 papers (48%) published between 2021 and 2024. This trend reflects a growing academic interest in applying neural networks to tackle the challenges of intermittent demand. The noticeable rise after 2020 aligns with global advancements in DL and forecasting tools.

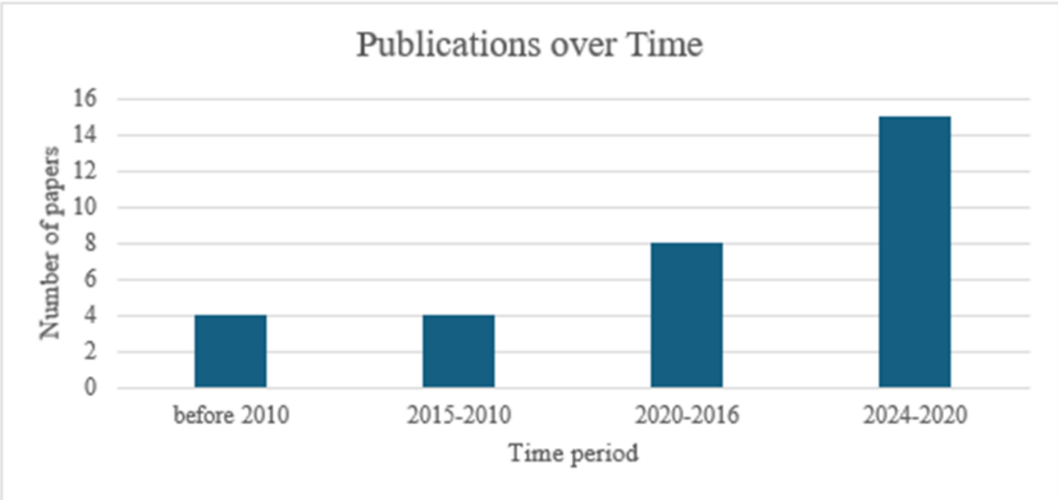

Fig. 6: Publications over Year

4.1.2. Country of origin

Error! Reference source not found. illustrates the geographic distribution of the reviewed literature based on the first author's affiliation. The top contributing countries were:

- The United States, Germany, Turkey, and India.
- Followed by France, Korea, Indonesia, and Poland, each published fewer articles.
- Countries such as China, Italy, Brazil, and Canada are represented by a single publication.

This distribution reflects the broad geographic spread and reinforces the global relevance of spare parts management, as well as the need for advanced forecasting methods worldwide.

4.1.3. Application Domains

Error! Reference source not found. illustrates the distribution of the 30 reviewed articles across various application domains. The most significant number of studies (20%) focused on the automotive sector, where predicting spare parts is crucial for maintenance. Also, 20%

of the articles emphasized the retail industry, using Kaggle M5 competition dataset provided by Walmart. Aircraft (13%), Electronics (10%), Manufacturing (7%), Military (7%), and Bus Fleet (7%) were also represented, reflecting the importance of this topic in critical industries. The limited attention given to oil and gas (3%) and petrochemicals (3%) sectors suggests a valuable opportunity for further research.

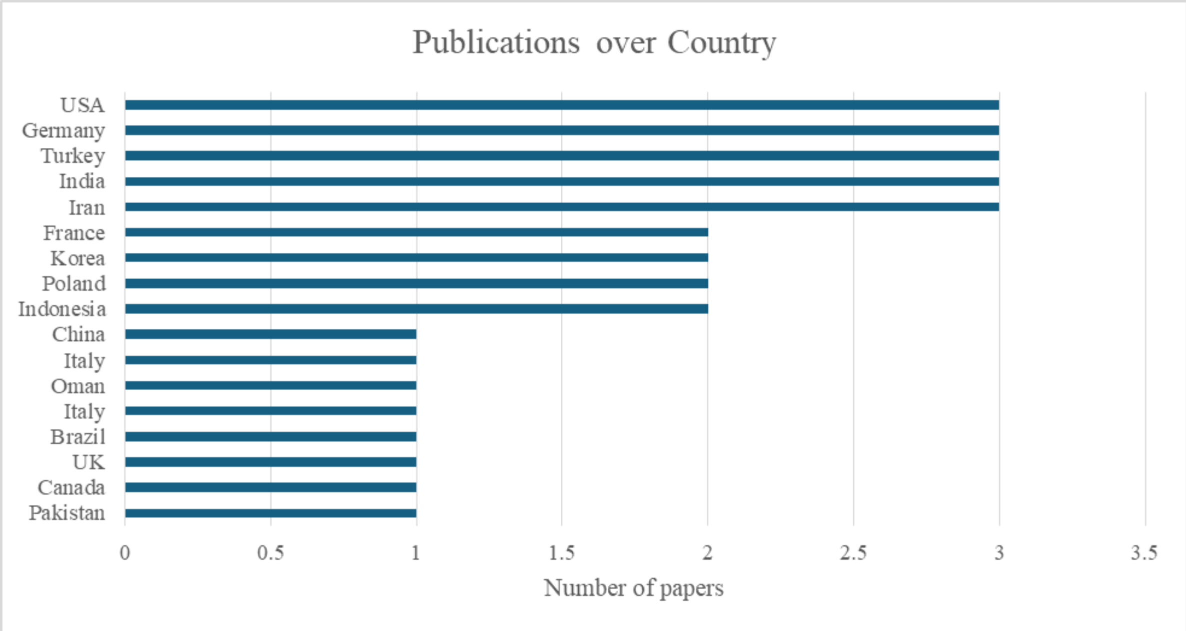

Fig. 7: Publications over Country

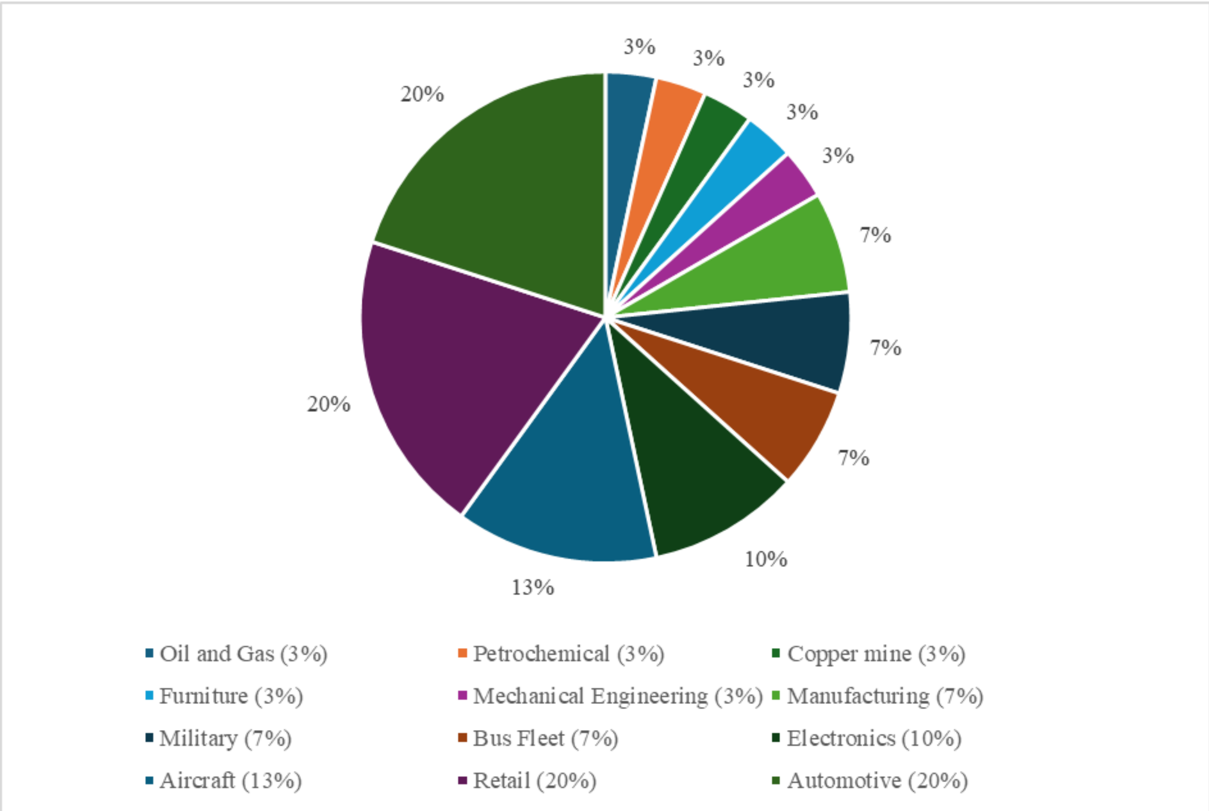

Fig. 8: Application Domains in Literature

4.1.4. Forecasting Methods Used

Various models have been implemented in the literature for forecasting spare parts using neural networks. We will cover each of them in the following subsection. This paper examines the research papers reviewed here in terms of the methods used and the most effective approach. Fig. 7 illustrates the classification of forecasting methods. Table 1 summarizes the reviewed papers in the literature, categorized by the technique used.

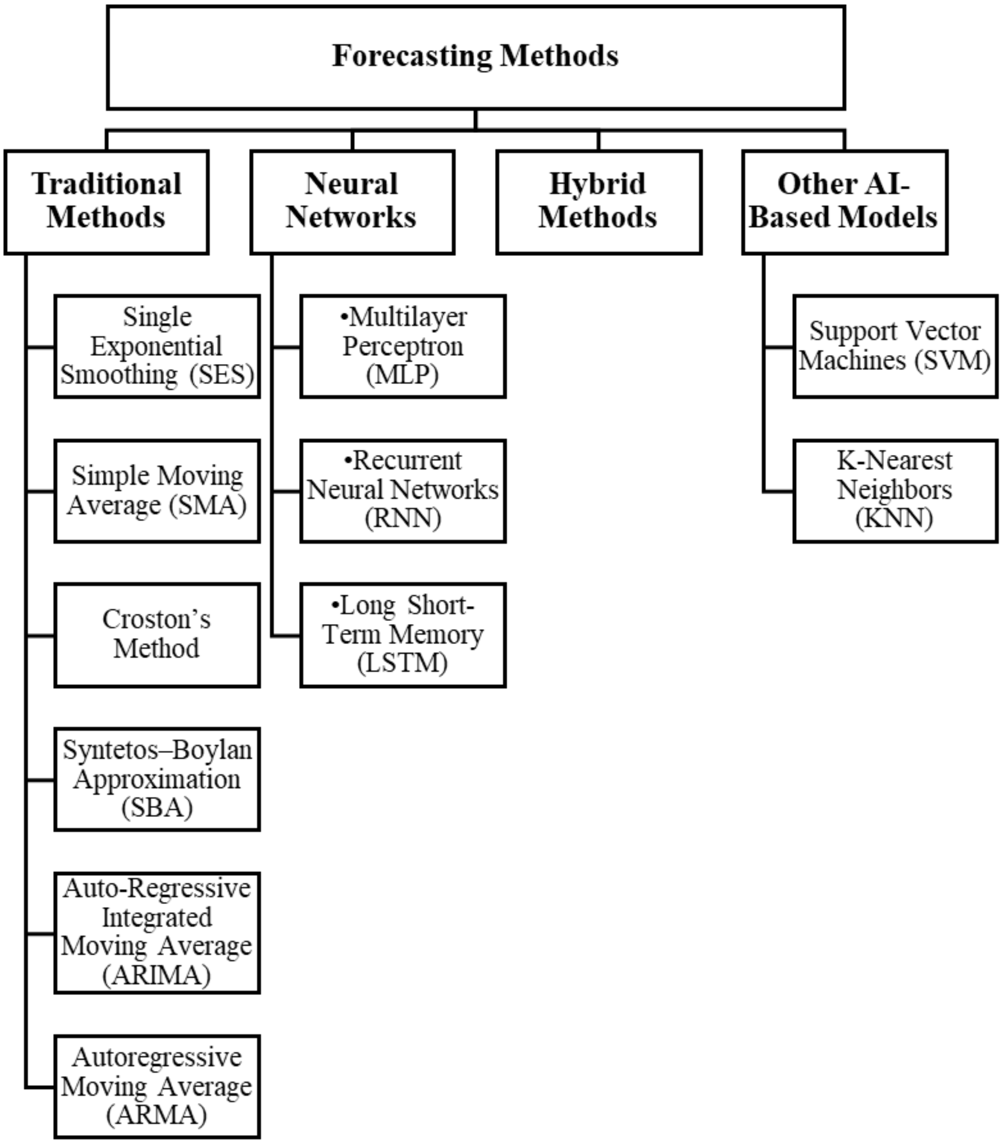

Fig. 7: Classification of forecasting methods through literature

Recent studies have demonstrated the effectiveness of ANNs, particularly MLPs and RNNs, in forecasting intermittent demand. In the studies [16, 22], the authors proposed using MLP as an alternative to traditional forecasting techniques, including Single Exponential Smoothing (SES), Croston's method (CR), and the Syntetos–Boylan Approximation (SBA). Subsequent benchmarking studies confirmed that neural network (NN) models generally outperform these conventional methods. In another context, RNNs were applied to forecast spare parts demand in a petrochemical company, with results showing superior performance over both CR method and the SBA approach [23].

A hybrid forecasting approach integrating regression modeling, information criteria, and ANNs was introduced in [24], where eight forecasting techniques—traditional, hybrid, and NN-based—were evaluated. The hybrid model demonstrated the highest accuracy. Similarly, [25] evaluated ANN-based models, including MLP and RNN, against CR-based methods, , with results indicating the superiority of ANN approaches. In the study [14], neural networks were assessed against benchmarks, including the Simple Moving Average (SMA), SES, CR, and its variants. Findings indicated the efficacy of NN models for intermittent demand scenarios. The work [13] examined the application of MLP and RNN models in spare parts forecasting and confirmed their advantage over CR method and ARIMA.

The study [26] used MLP with a backpropagation (BP) algorithm and tested four scenarios (M-S1 to M-S4) using various combinations of input features and stock-keeping units (SKUs). Results indicated that the MLP model, especially in M-S1 and M-S3 scenarios, outperformed all other methods. Also, [17] evaluated a single-hidden-layer NN against CR-based models and observed improved forecast accuracy. In [27] three novel hybrid models, AI-based methods (ANN and SVM) were combined with traditional techniques. These were benchmarked against nine classical methods, including SES, SMA, and SBA; the hybrid models consistently delivered superior results. The hybrid ARIMA–ANN model achieved the best performance, underscoring the value of integrating statistical and AI-based methods for capturing nonlinear demand patterns, particularly in the presence of incomplete or unreliable data.

Further advancements were introduced in the study [19], which presented new NN models that outperformed SES, CR, SBA, and bootstrap-based methods, as well as the NN model from [16]. In the study[28], an LSTM network was proposed to manage highly volatile demand data. Its performance surpassed that of ARIMA, SES, and other AI models. In the study [8] , hybrid combinations of ARMA, SES, and MLP were investigated, while in the study, [29] it was demonstrated that RNN and deep neural networks (DNN) outperformed CR and SES. Moreover, in [30], the authors explored forward and bidirectional LSTM networks for demand forecasting, concluding that the bidirectional variant provided superior accuracy compared to both unidirectional LSTM. In the study [31], deep learning models were benchmarked against Random Forest (RF), gradient-boosted trees, and SVM, with results indicating that deep learning yielded the highest accuracy and the lowest runtime. Finally, in [32], an RNN/LSTM framework was proposed for demand forecasting for spare parts of automobiles, demonstrating superior forecasting accuracy compared to existing methods.

Table 1: Reviewed papers based on the method used

Paper	Year	Method Used				
		DL	MLP	RNN	LSTM	Hybrid
[33]	2007		✓			
[16]	2008		✓			
[23]	2008			✓		
[22]	2008		✓			
[24]	2013		✓			✓
[25]	2013		✓	✓		
[14]	2013		✓			
[13]	2015		✓	✓		

Paper	Year	Method Used				
		DL	MLP	RNN	LSTM	Hybrid
[26]	2017		✓			
[17]	2017		✓	✓		
[27]	2020					✓
[19]	2020		✓			
[28]	2020				✓	
[8]	2021					✓
[29]	2021	✓		✓		
[30]	2021				✓	
[31]	2021	✓				
[32]	2021	✓			✓	
[21]	2021	✓	✓		✓	
[34]	2022		✓			
[35]	2022	✓			✓	
[36]	2022	✓			✓	
[37]	2023	✓	✓	✓	✓	
[38]	2023	✓	✓	✓	✓	
[39]	2023	✓			✓	
[40]	2023		✓			
[41]	2024		✓	✓	✓	

4.5. Case Studies and Dataset Handling

When analyzing the case studies in the literature, it was found that a diverse range of industries apply intermittent demand forecasting, including the manufacturing sector, such as chocolate, toner cartridges, furniture, and electronics. Most of the addressed papers applied their model to aircraft spare parts. The variety of industries shows the adaptability of forecasting models to different fields. Most of the papers span a period length of the datasets using months (M). It is the most used unit. Addressing monthly demand is common in intermittent demand forecasting. Most studies use 80%-20% splits, a widely used data split practice in machine learning. Table 2 highlights the evolution of practices in dataset handling across different fields and the data splitting strategies employed.

Table 2: Classification of papers according to dataset sources/ industries, the addressed data period, and the data split strategies

Paper	Year	Dataset source	No. of Periods*	Data sets split (Training/ Testing)
[16]	2008	An electronics distributor	967 D	N/A
[23]	2008	Petrochemical Company	67 M	55 M – 12 M
[22]	2008	An electronics distributor	967 D	**80% –20%** 65%–35% 50%–50%
[25]	2013	Aircraft Maintenance, Repair & Overhaul (MRO) company	62 M	60% - 18% (Validation) - 22%

Paper	Year	Dataset source	No. of Periods*	Data sets split (Training/ Testing)
[14]	2013	Automotive Industry	236 M	Training: 36 M Burn-in period: 100 M Testing: 100 M
[13]	2015	A real company from the sector of electronic equipment	N/A	70%- 30%
[26]	2017	Dassault Aviation	48 M	N/A
[17]	2017	Automotive Industry	24 W	65%–35%
[27]	2020	An underground copper mine	N/A	N/A
[19]	2020	An airline company	123 M	80 M: within sample 43 M: out of sample
[28]	2020	A furniture company	132 M	**80% - 20%**
[42]	2020	An aircraft manufacturer	944 I	N/A
[8]	2021	Automotive Industry	24 W	65% - 35%
[31]	2021	Data Co supply chain dataset (Kaggle)	N/A	N/A
[37]	2023	Central Aviation Spares Depot (CASD)	24 Q	**80% - 20%** Validation: 20% of Training
[39]	2023	A complex manufacturing enterprise	30 M	Training: (M1 – M30) Validation: (M2 – M29) Test: (M3 – M30)
			34 M	Training: (M1 – M32) Validation: (M2 – M33) Test: (M3 – M34)
[40]	2023	Bus fleet	N/A	7 years - 1 year
[43]	2024	Bus fleet	N/A	70% - 30%

*I: Instances, D: Days, W: Weeks, M: Months, Q: Quarters

4.2. Bibliometric Network Analysis

To investigate the thematic structure of the reviewed papers, a bibliometric network analysis was conducted using VOSviewer [44]. The analysis utilized bibliographic data exported from the Web of Science Core Collection, including full records and cited references. Two types of network maps were generated:

- A document-level bibliographic coupling map, which clusters papers based on shared references.
- A keyword co-occurrence map, which visualizes frequently used terms across the literature.

4.2.1. Bibliographic Coupling

A bibliographic coupling analysis was performed to examine the relationship between papers based on the number of references they share. The resulting map (Fig. 8) identified five distinct clusters, each representing a major research direction in the literature. Fig. 8 displays the bibliographic coupling map, where nodes represent individual documents and links represent the strength of shared references. The size of the nodes reflects the strength of citation links, and the color indicates cluster membership. Table 3 illustrates the five thematic clusters, highlighting their corresponding research themes, colors as shown in Fig. 8, and the papers grouped in each cluster.

Table 3: Summary of Clusters Identified in Bibliographic Coupling Analysis

Cluster	Theme	Color (Fig. 8)	Papers included
1	AI-Based Forecasting for Spare Parts	Red	[26, 27, 29, 32, 37, 40, 41]
2	Hybrid and Transfer Learning Approaches	Green	[28, 35, 36, 38, 39]
3	Comparative Forecasting using Statistical and ML Methods	Blue	[8, 19, 21, 33, 45]
4	Lumpy Demand Forecasting with Neural and Heuristic Methods	Yellow	[22, 23, 46]
5	Inventory-oriented Evaluation of Neural Networks	Purple	[13]

4.2.2. Keyword Co-occurrence Analysis

A keyword co-occurrence analysis was performed to discuss frequently discussed concepts in the literature. Keywords appearing in five or more papers were grouped into clusters, highlighting the core themes and recurring concepts within the literature. Fig. 9 presents a co-occurrence map based on author keywords, where node size indicates the frequency of keywords and link strength reflects co-mentioning across multiple papers. The most used keywords were “intermittent demand”, “demand forecasting”, “spare parts”, “forecasting”, “neural networks”, and “deep learning”.

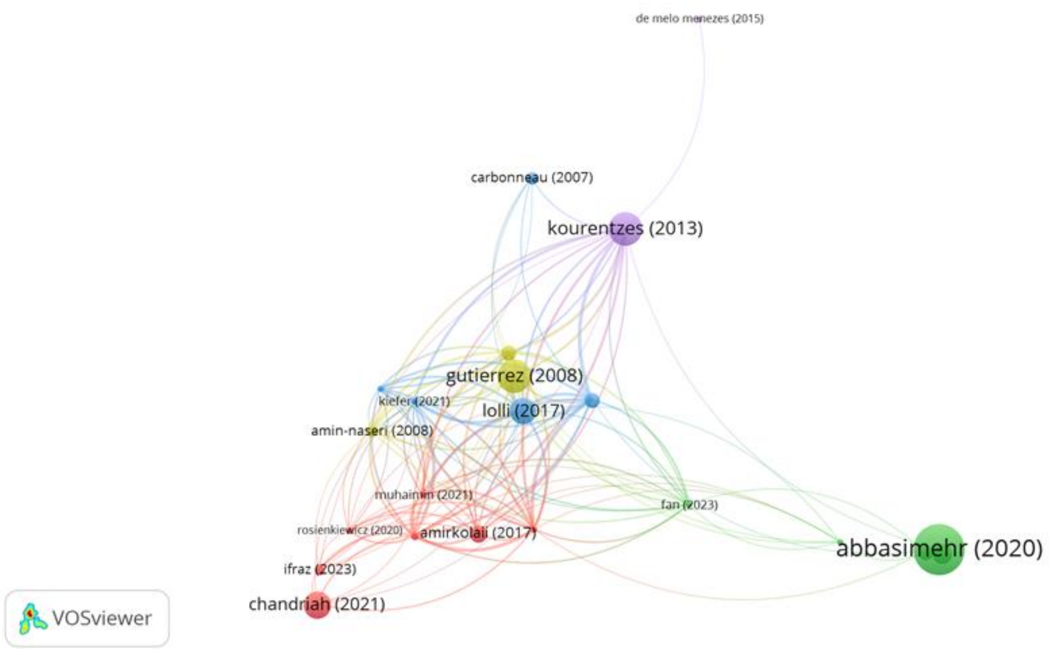

Fig. 8: Bibliographic Coupling Map of Documents

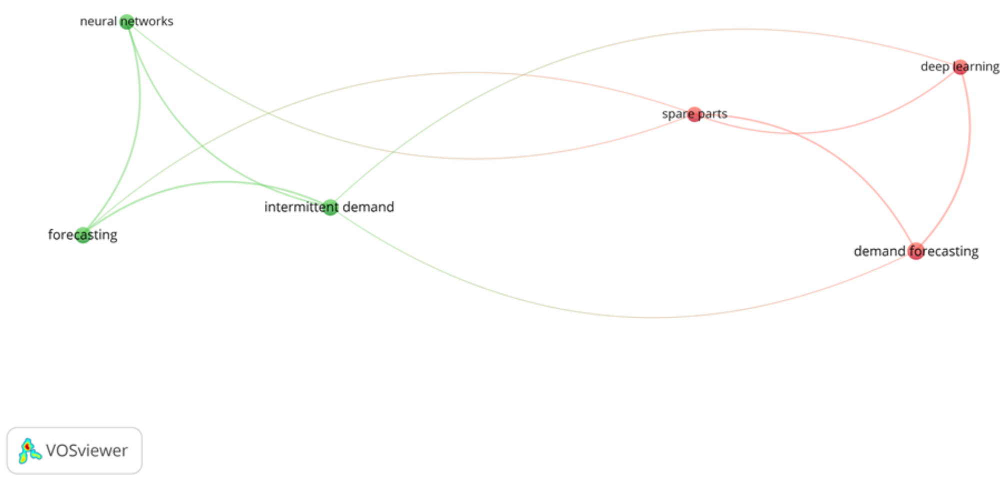

Fig. 9: Co-occurrence Map based on Author Keywords

5. Feature selection in neural networks

In neural networks, features are the variables or attributes derived from the dataset that serve as inputs to the model. Each input node in the network corresponds to a specific feature. In the context of demand forecasting, these features are often constructed from historical demand data. **Table 4** presents the identified features for intermittent demand, as addressed in the literature.

Table 4: Addressed features through literature

Paper	Feature1	Feature2	Feature3	Feature4	Feature5
[16]	✓		✓		
[22]	✓		✓		✓
[14]	✓	✓	✓		
[17]	✓		✓		✓
[19]	✓	✓	✓	✓	

To improve the forecasting accuracy of intermittent demand, particularly for spare parts, it is essential to select features that capture demand patterns and zero-demand occurrences that indicate the sporadic nature of spare parts. The following features are based on historical demand sequences. Below is a description of the key features used in literature:

- Feature 1: The demand value observed directly before the target the period (Lag 1).
- Feature 2: The demand values observed at several time steps before the target period (LagN).
- Feature 3: No. of periods between the two most recent non-zero demand occurrences preceding the target period (NZ).
- Feature 4: No. of periods since the most recent zero demand occurrence prior to the target period (FZ).
- Feature 5: The cumulative no. of consecutive zero demand periods immediately before the target period.

For example, Babai et el., 2020 [19] proposed a neural network structure composed of only one hidden layer. The hidden layer is composed of three neurons. They used four input features. **Error! Reference source not found.** shows their proposed NN structure. They proposed five architectures, each varying in the combinations of features, as detailed in **Table 5**. To evaluate the model, they used 3,5, and 9 nodes in the hidden layer.

Their results show that the architecture incorporating lag 1, NZ, and FZ with three neurons in the hidden layer achieved the best performance according to the mean absolute scaled error. In contrast, the architecture, incorporating lag 2, NZ, and FZ, with five neurons in the hidden layer, achieved the best performance in terms of the scale-free mean squared error.

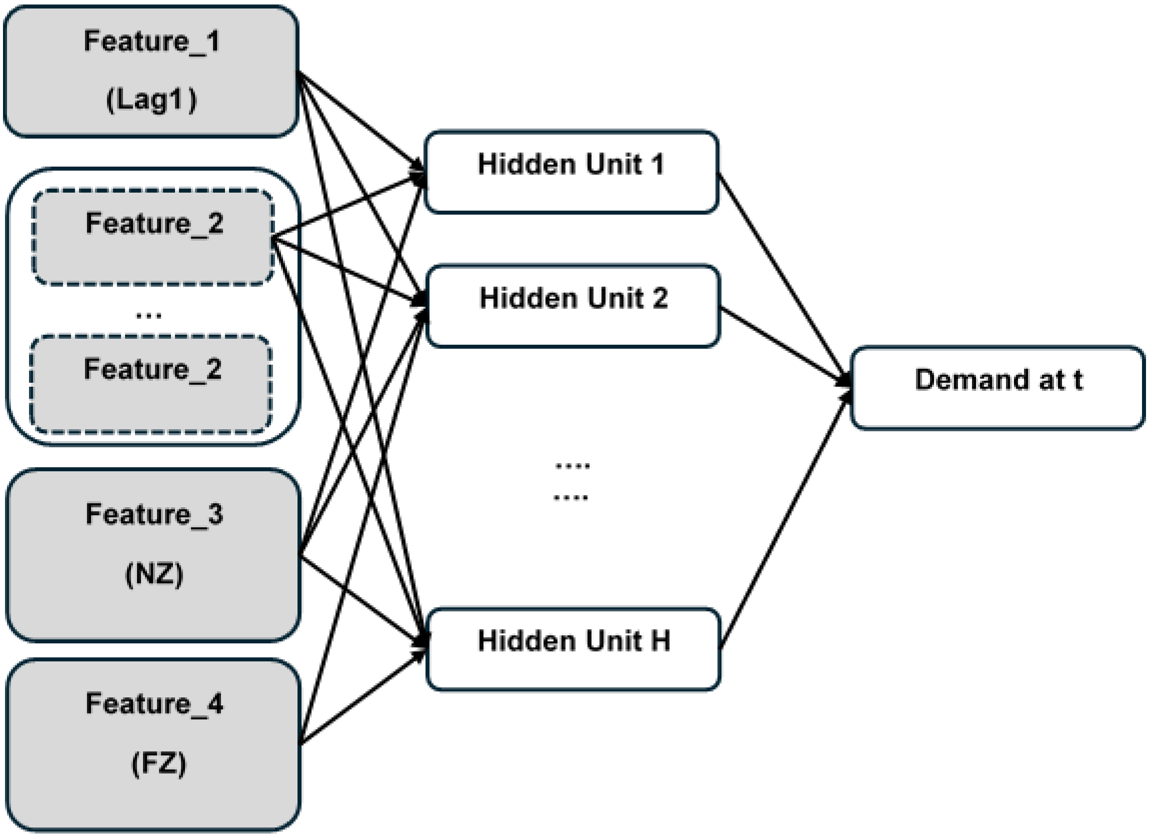

Fig. 12: NN structure proposed by [19]

Table 5: Architectures proposed by [19]

Paper [19]	Feature_1 **(Lag 1)**	Demand $_{t-1}$	Feature_2 **(Lag N)**	Demand $_{t-2}$	Demand $_{t-3}$	Feature_3 **(NZ)**	Feature_4 **(FZ)**
Architecture1:	✓	✓					
Architecture2:	✓	✓	Lag 2	✓		✓	
Architecture3:	✓	✓	Lag 3	✓	✓	✓	
Architecture4:	✓	✓				✓	✓
Architecture5:	✓	✓	Lag 2	✓		✓	✓

6. Forecast Accuracy Measures

These measures are essential to evaluate the performance of forecasting, particularly in assessing how closely the forecasted values align with the actual observations. **Error! Reference source not found.** presents a comprehensive classification of forecast accuracy measures, systematically organized into four primary categories. This classification facilitates the selection of suitable evaluation criteria according to the nature of the data. First, absolute error measures quantify errors in the same units of the actual data. Second, percentage error measures express forecast errors as proportions of actual values. Third, relative-error measures assess model performance relative to a benchmark. Finally, scale-free metrics enable comparisons across time series of different scales, making them particularly useful in forecasting intermittent demand.

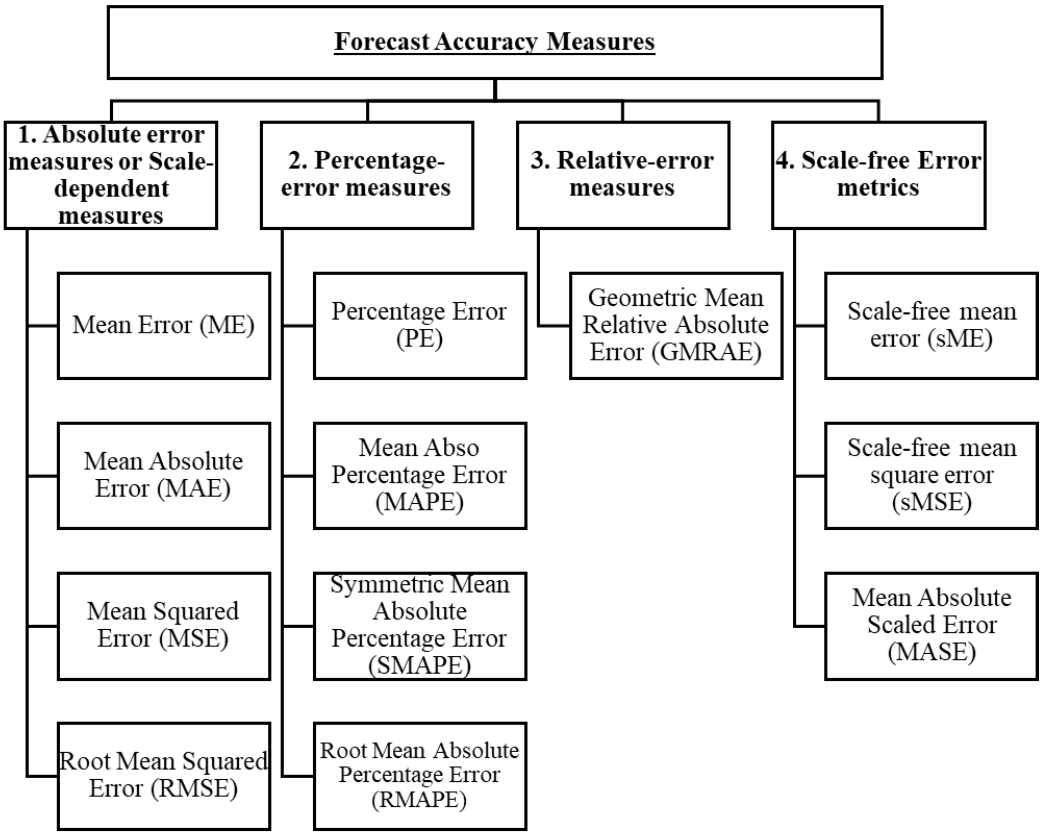

Fig. 13: Classification of forecast accuracy measures

In the context of the formulas provided below for different error measures in demand forecasting:

$\boldsymbol{t}$ No. of instances of the actual and the corresponding forecasted values.

$\boldsymbol{Actual_i}$ Actual demand (at period i)

$\boldsymbol{Forecast_i}$ Forecasted demand (at period i).

5.1. Scale-dependent measures

They refer to metrics that are sensitive to the scale or level of demand. They are used in comparing between various methods applied on the same datasets [47]. They include:

ME is a very straightforward measure. Simply, it is the mean or average of the differences between the actual values and the forecasted values across a given time period. ME is calculated as follows in Eq. 1:

$$ME_t = mean\ (Actual_i - Forecast_i) = \frac{1}{t}\sum_{i=1}^{t}(Actual_i - Forecast_i) \qquad \text{Eq. 1}$$

While the ME provides simple accuracy, it has a significant drawback; it considers the sign of the error. As a result, a model with equal amounts of over or – and underestimation could have a Mean Error close to zero, even though it may not be providing accurate predictions [48]. Here, MAE takes the '*absolute'* value of each error before averaging. This prevents positive and the negative errors from cancelling one another. MAE is somehow similar to ME but it takes an '*absolute*' value. MAE is calculated as follows in Eq. 2:

$$MAE_t = mean\ (|Actual_i - Forecast_i|) = \frac{1}{t}\sum_{i=1}^{t}|Actual_i - Forecast_i| \qquad \text{Eq. 2}$$

MSE calculates the mean of the '*squared'* differences between the actual values and forecasted values. Unlike MAE, MSE amplifies the impact of significant errors. The MSE is calculated as follows in Eq. 3:

$$MSE_t = mean\ (Actual_i - Forecast_i)^2 = \frac{1}{t}\sum_{i=1}^{t}(Actual_i - Forecast_i)^2 \qquad \text{Eq. 3}$$

RMSE is computed by taking the square root of MSE as in Eq. 4. The square root's objective is to convert the error measure back to the original data scale, so it has the same unit as the original data.

$$RMSE_t = \sqrt{MSE_t} \qquad \text{Eq. 4}$$

5.2. Percentage-error measures

PE calculates the % difference between the actual values and forecasted values, and expressed in Eq. 5 as a percentage multiplied by 100.

$$PE_i = \frac{Actual_i - Forecast_i}{Actual_i} \times 100\% \qquad \text{Eq. 5}$$

MAPE, as expressed in Eq. 6, is the average percentage error between the actual values and forecasted values, providing a percentage-based measure of forecasting accuracy. The MAPE is not suitable for intermittent demand because the actual demand often has zero values; in other words, the denominator in these cases is zero [29].

$$MAPE_t = mean\ \left|\frac{Actual_i - Forecast_i}{Actual_i}\right| = \frac{1}{t}\sum_{i=1}^{t}\left|\frac{Actual_i - Forecast_i}{Actual_i}\right| \times 100\% \qquad \text{Eq. 6}$$

SMAPE is another percentage-based measure that addresses some of the limitations of MAPE, especially when dealing with minor or zero values. In sMAPE, the divisor is computed as half the sum of the actual values and the forecasted values [49]. It is expressed in Eq. 7.

$$SMAPE_t = \frac{1}{t}\sum_{i=1}^{t}\left|\frac{Actual_i - Forecast_i}{\frac{1}{2}(Actual_i + Forecast_i)}\right| \times 100\% \quad \text{Eq. 7}$$

RMAPE, as expressed in Eq. 8, is the mean of the squared percentage differences between the absolute actual values and the forecasted values. The square root converts the error measure back to the data's original scale.

$$RMAPE_t = \sqrt{mean\left(\frac{Actual_i - Forecast_i}{Actual_i}\right)^2} = \sqrt{\frac{1}{t}\sum_{i=1}^{t}\left(\frac{Actual_i - Forecast_i}{Actual_i}\right)^2} \times 100\% \quad \text{Eq. 8}$$

5.3. Relative-error measures

GMRAE provides a multiplicative average of the percentage errors and is less sensitive to outliers.

The symbol ∏ (uppercase pi in Greek) represents the product operator. It is used to denote the product of a sequence of terms. In the formula shown for GMRAE (Eq.9), the product operator ∏ is applied to a sequence of relative absolute errors.

The product operator (∏) in the GMRAE formula is used to calculate the product of the relative absolute errors across all observations, and the geometric mean is then derived by taking the t^{th} root. This measures the average relative error, considering the multiplicative nature of errors across different observations.

GMRAE is useful in demand forecasting when the demand is intermittent, or has many zero values. Traditional error measures may not perform well in such situations, and GMRAE offers an alternative perspective by using a geometric mean.

$$GMRAE = \left(\prod_{i=1}^{t}\frac{|Actual_i - Forecast_i|}{|Actual_i|}\right)^{\frac{1}{t}} \times 100\% \quad \text{Eq.9}$$

5.4. Scale-free Error Metrics

Scale-free measures in forecasting are evaluation metrics designed to be less sensitive to the scale of the data, making them suitable for benchmarking forecast accuracy using different datasets. These metrics help address the challenge of comparing models on datasets with varying demand levels or variability. Some standard scale-free measures in forecasting include sME and sMSE. They are expressed in Eq. 10 and Eq. 11 respectively. The key difference between sMSE and MSE lies in their normalization by the mean of the actual values. sMSE scales the errors using the mean of the actual values. This scaling allows for better comparability of forecast accuracy using different datasets with different scales.

$$sME = \frac{1}{t}\sum_{i=1}^{t}\frac{Actual_i - Forecast_i}{Actual_i} \quad \text{Eq. 10}$$

$$sMSE = \frac{\frac{1}{t}\sum_{i=1}^{t}|Actual_i - Forecast_i|}{\frac{1}{t-1}\sum_{i=2}^{t}|Actual_i - Actual_{i-1}|} \quad \text{Eq. 11}$$

Unlike some traditional accuracy metrics, MASE accounts for the seasonality and trend in the data. MASE provides a measure of forecast accuracy scaled by MAE (as in Eq. 2) of a simple forecast, typically the naive forecast (using the actual value from the previous period). So, the MASE is expressed as follows in Eq. 12:

$$MASE = \frac{\frac{1}{t}\sum_{i=1}^{t}|Actual_i - Forecast_i|}{\frac{1}{t-1}\sum_{i=2}^{t}|Actual_i - Actual_{i-1}|} \quad \text{Eq. 12}$$

Hyndman and Koehler, 2006 [47] compared the performance measures of time series forecasting. They proposed that MASE should be the standard measure for forecast accuracy. Table 6 shows the classification of papers according to their forecasting performance measures.

Table 6: Classification of papers according to their forecasting performance measures

Paper	**(1)**	**(2)**	**(3)**	**(4)**
[33]	MAE			
[16]		MAPE		
[23]		A-MAPE	PB	MASE
[22]		MAPE	PB	RGRMSE
[24]	RMSE		*ex post*	
[14]	ME			
	MAE			
[13]	RMSE	MAPE		
[26]	MSE			
[17]		MAPE	ME/A	
[27]			*ex post*	
			R^2	
[19]				sME & sMSE
[28]	RMSE	S-MAPE		
[42]	RMSE			
[21]				MASE
[8]			ME/A	
[29]	MAE			
[30]	MAE			
	RMSE			
[31]	MAE			
[32]	ME			
	MSE			
[35]	ME			
	MAE			
	RMSE			
[36]	MAE	MAPE	R^2	
[37]	MAE			MASE
[40]		MAPE		

A-MAPE: Adjusted MAPE, PB: Percentage Better, ME/A: ME divided by Average
R^2: Coefficient of Determination, RGRMSE: Root Geometric Root MSE

7. Research Gaps and Future Work

According to the literature review, various research directions have been identified, particularly through an analysis of the latest research papers published since 2020. The potential of using hybrid models that combine traditional forecasting techniques with AI-based approaches was proposed in [27]. The author suggested exploring additional variables and enhancing the integration of nonlinear patterns to achieve better forecasting accuracy. She also proposed testing hybrid models in different industries for more generalized results.
Future research could examine the use of hybrid intelligent models, such as ANFIS, which combine NNs with fuzzy logic. These models are suitable for handling nonlinear relationships and uncertainty. For example, the authors [50] successfully applied a hybrid ANFIS-regression framework to predict quality outcomes in a manufacturing environment with complex variable interactions.
Applying the method to other domains, such as customer behavior prediction, is also recommended [28]. The use of different deep learning methods is also suggested, such as attention-based neural networks. In the study [19], the authors proposed further investigation into incorporating both forecasting and also inventory performance of the NN methods. They also proposed categorizing the methods of forecasting according to the demand's characteristics. To derive more generalized and conclusive results, it is recommended that other demand data sets be incorporated to broaden the research. They recommended investigating the impact of the length of the historical data on the performance of the models. That study could identify an empirical minimum demand history length or a threshold where NN methods will outperform more straightforward parametric techniques. In the study [37], further research was recommended for predicting spare parts demand in the aviation industry. This will enhance the availability of aircraft.
In [40] the authors suggested comparing the forecasting performance against other forecasting methods and analyzing new variables that affect demand, thereby increasing forecasting accuracy. Developing decision support systems was proposed [43]; this can utilize failure patterns deduced from their model to be used dynamically as input for scheduling corrective maintenance. Those systems can be developed for demand forecasting for identifying safety stock of spare parts and calculating their reorder points. It is recommended that vehicles be classified according to several factors, such as age, operating region, and geographical conditions, to discover distinct sequential patterns. It can be considered not only to consider past demand but also to consider the failure data of spare parts. It is recommended to weigh the failures according to their importance. It is a valuable research point to introduce weights to failures based on their criticality and integrate this into the analysis. In both studies [40, 43], the authors recommended applying their findings to maintenance and repair units in fields other than bus fleets.

8. Proposed Solution Framework

In response to the research gaps identified in recent studies, this study recommends the use of a hybrid forecasting framework tailored for intermittent demand forecasting. In addition to lag-based features, it is proposed to emphasize richer and informative features. To ensure the effectiveness of the proposed hybrid framework, the evaluation strategy incorporate both forecasting accuracy and Inventory performance. This dual evaluation is critical for spare parts management, where forecasting errors can lead to costly stockouts or er excessive holding costs.

9. Conclusions

This literature review highlights the advancements in forecasting intermittent demand for spare parts using ANN and DL techniques. Traditional forecasting methods often fail to capture the nonlinearities in the intermittent demand pattern. ANNs and DL approaches, particularly FNNs, RNNs, and LSTM networks, demonstrate significant promise in effectively overcoming the addressed problem by utilizing them in nonlinear and sequential data relationships. This study reveals the outstanding performance of ANN and DL models over the traditional methods, particularly in the case of high variability and irregular, nonlinear demand. Hybrid approaches that combine conventional forecasting with ANN-based methods further enhance model performance, highlighting the importance of integrating multiple techniques.

Challenges include the need for large, reliable datasets to achieve optimal performance. Future research should address these limitations by exploring data augmentation feature selection, expanding the application of these methods to various industries, and incorporating multiple variables, such as maintenance schedules and operational environments, that can further enhance the generalizability of forecasts.

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