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Intermittent demand forecasting of aircraft components through installed base forecasting: a case study

Indexed by: Web of Science Group

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Highlights

- Study improves forecasting of intermittent demand for aircraft components.
- Installed base data enhances accuracy of component demand forecasts.
- Delphi method identifies key aviation specific forecasting factors.
- Neural network model outperforms the traditional Croston method.
- Higher forecast accuracy supports more effective aircraft maintenance.

Abstract

This research addresses the inefficiencies in traditional forecasting methods for the intermittent and erratic demand for aircraft components, which typically results to either high inventory costs or expensive aircraft-on-ground situations from stockouts. The main objective is to build an enhanced forecasting model that uses installed base information to improve demand forecasting accuracy for aircraft components. An extensive literature review followed by a Delphi method study is used to identify the significant contextual factors impacting the demand and integrated into an Artificial Neural Network (ANN) forecasting model. The model's performance is evaluated using Mean Squared Error and benchmarked against the Croston method. This research provides efficient forecasting practices to the airline industry, probably reducing the operating expenses and improving the service quality.

Keywords

aircraft components, spare parts, demand forecasting, installed base, forecasting model, artificial neural network

1. Introduction

Air transport carries millions of people and enormous volumes of cargo annually worldwide, functioning as the cornerstone of global connectivity and playing an integral role in the international economy. To manage and operate this large scale and complicated transportation network, airlines throughout the globe deploy massive fleets of aircrafts, with many different types of aircraft models, each uniquely suited to catering to particular routes and cargo demands. Behind every successful flight operated by these aircrafts lies an extended network of airline engineering supply chain; an advanced network consisting of suppliers, maintenance staff and logistics specialists. Efficient management of the airline engineering supply chain is crucial for the availability of aircraft components, tools, and materials, ensuring the safety and airworthiness of the fleet. Given the high safety requirements and operational complexity of aviation systems, applying the suitable evaluation approach to aircraft spare parts can significantly enhance reliability centered maintenance and minimize the risk of unscheduled downtime as well [1]. What is more the importance of spare parts management is demonstrated by the scale of this area – for example according to the Spare Parts Product Market Report 2025 (Global Edition)

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[2], the value of the global spare parts market amounted to USD 529.53 billion in 2021 and is expected to reach USD 639.57 billion by the end of 2025. The author forecasts that by 2033 the market will grow to USD 933.00 billion, corresponding to a compound annual growth rate (CAGR) of 4.83% over the period 2025–2033.

In contrast, the Aerospace Parts Manufacturing Global Market Report 2025 [3] indicates that the value of the aerospace parts manufacturing market will increase from USD 981.27 billion in 2024 to USD 1,021.81 billion in 2025, at a compound annual growth rate (CAGR) of 4.1%. Moreover, forecasts point to continued dynamic growth – by 2029 the market is expected to reach USD 1,240.75 billion, which represents a CAGR of 5.0%.

Aircraft component demand forecasting is a key aspect of airline engineering supply chain management. Among the four inventory categories of aircraft components, consumables and expendables demonstrate a consistent demand pattern and adhere to an inventory replenishment cycle centered around maintaining a reorder point. On the contrary rotables and repairables exhibit erratic, lumpy, or intermittent demand patterns involving long series of zero-demand periods [4]. The demand pattern may result from the fact that aviation accidents are rarely predictable and often irreversible [5]. Demand forecasting for commercial aircraft components poses a unique difficulty due to these characteristics commonly found in the demand for rotables and repairables and make traditional forecasting methods less effective.

Even though specialized studies into the field of aircraft component demand forecasting are fairly limited, an extensive body of literature exists on the subject of spare parts demand forecasting. These established approaches generally utilize time series forecasting methods. Hence, there is a need for research to investigate a method which combines and integrates a broad set of demand drivers [6]. Furthermore, a research gap for incorporation of contextual information about the installed base into spare part demand forecasting also exists [4]. Current literature lacks exploration of the use of contextual forecasting methods specifically tailored to address the intermittent demand patterns of aircraft components.

Accurate forecasting of aircraft spare-parts demand is essential for ensuring fleet airworthiness, reducing maintenance delays, and enabling cost-efficient inventory planning in aviation operations [7]. Installed based forecasting under contextual forecasting methods, which incorporate factors beyond historical demand data, hold significant promise in improving the accuracy of forecasts. This research endeavour focuses on achieving two research objectives, 1. Analyze contextual factors to be considered when using installed base forecasting for aircraft components, 2. Develop a forecasting model incorporating all the analyzed factors to forecast intermittent demand of aircraft components.

This research aims to improve demand forecasting accuracy in the airline engineering supply chain by examining installed base forecasting and contextual factors beyond historical data. This will lead to operational excellence, safety, efficiency, cost management, and customer satisfaction. While the empirical validation is conducted within a single airline case study, the proposed methodological framework may provide conceptual guidance for other high-value, reliability-driven industries characterized by intermittent demand and installed base dynamics. The research outcomes may contribute to improving engineering supply chain management by supporting more accurate demand forecasting, which in turn may reduce operational disruptions and improve cost efficiency and reliability. The aviation industry is interconnected, and improved forecasting could lead to rippling effects, reducing lead times, boosting efficiency, and even enabling breakthroughs in aircraft design and manufacture. The research's relevance extends beyond individual airlines.

2. Literature review

Spare parts demand forecasting methods have two major categories: time series forecasting methods and contextual forecasting methods. Time series forecasting methods rely on historical demand data while contextual forecasting methods are influenced by contextual factors.

2.1. Time series spare part demand forecasting methods

Spare parts display unpredictable, lumpy, or intermittent demand patterns with extended series of zero demand periods. Thus, typical forecasting techniques of time series such as exponential smoothing or moving average generally fail to anticipate demand effectively in these cases since they place a major weight on recent data points [4].

Croston proposed an alternative approach to forecasting inter demand intervals and demand sizes using exponential smoothing methods. The projections are updated during positive demand times and averaged to estimate demand per unit of time [8]. The Croston method has become a primary benchmark for forecasting in this field.

Syntetos and Boylan proposed the Syntetos-Boylan approximation (SBA) as a modified strategy to correct the positive bias in Croston and introduced a modified strategy by presenting an analytical approximation method to correct the bias [9]. Using a dataset from the automobile sector, they show that SBA provide more accurate conclusions than Croston, for swiftly intermittent demand [10]. Another variation is the Teunter-Syntetos-Babai (TSB) model, which exponentially smooths demand likelihood and magnitude after every positive demand [11]. However, simulation research done utilizing automotive datasets demonstrates that TSB does not lead to considerably more accurate projections than other approaches [12]. Based on this Babai suggested a new strategy referred to as modified SBA to overcome TSB's flaws with industrial datasets. The modified SBA's forecast updates are equivalent to those of SBA during positive demand periods, but when the risk of obsolescence develops, the updates become similar to those of TSB [13].

In recent years, there has been a significant increase in the number of publications devoted to hybrid forecasting [14]. This concept is developed to improve forecast accuracy compared to single models. It is assumed that combining several methods leads to better results than using them individually. As emphasized by Hajirahimi and Khashei, the literature identifies three key advantages of hybrid models: increasing forecast precision through comprehensive pattern capture and representation, reducing the risk of selecting an inappropriate model by integrating different forecasts, and facilitating the model selection procedure by using components of a diverse nature [14].

2.2. Contextual spare parts demand forecasting methods

Time series forecasting techniques rely on historical demand data, which may not accurately capture the unique characteristics of spare parts demand due to its variability and influence by factors like maintenance schedules, machine age, and operating conditions. Time series forecasting approaches include this extra contextual information primarily via historical data and, thus, may not immediately adapt to fluctuations in demand induced by these external causes [4]. Contextual forecasting approaches aim to address these issues by incorporating all relevant information, increasing the accuracy and responsiveness of spare parts demand forecasts. Research in contextual forecasting can be divided into judgmental forecasting and installed base forecasting.

Judgmental forecasting is a crucial method in spare parts forecasting, incorporating expert opinions and subjective insights to improve the reliability and accuracy of demand estimates. This approach is particularly useful when previous data is limited or unavailable, such as during the first stages of operation. Judgmental methods are often combined with statistical techniques to optimize results. A study on spare part demand in South Korea showed that this hybrid approach significantly improves results compared to conventional quantitative approaches [15]. Judgmental forecasting is essential for single period forecasting issues, but it relies heavily on the characteristics of the demand and how modifications are included in the forecasts [16]. However, some studies argue that judgmentally adjusted predictions may lead to inferior performance due to restricted access to quantitative information and reliance on subjective variables [17]. The accuracy of forecasts depends on the quality and experience of the individuals making the judgments.

The other forecasting approach in contextual forecasting, installed base forecasting, adds information about the installed base into the forecasting to deliver extremely precise spare part demand forecasts. The size and status of the installed base, status of the spare part, maintenance policy that decides when a component is replaced and environmental elements that effect the part's reliability is viewed as the key sources of information of the installed base that drive the spare part demand [6].

The use of installed base information in spare parts forecasting has gained popularity in recent years. In 90's Cohen suggested adding component failure rates and number of installed machines into exponential smoothing to improve demand estimations [18]. However, this method did not compare with other approaches. Later research by [19] provided approaches based on scheduled and corrective maintenance information. [20] also considered planned maintenance work in evaluating statistics from aircraft service providers and Netherlands railways. Simulations showed that these approaches performed better and created more accurate predictions than existing benchmark methods like SES, Croston, SBA, and TSB. [6] proposed a flexible approach that integrated maintenance schedule, age, installed base size, and parts reliability. Their simulation analysis showed that their solution outperformed SES and SBA and could achieve equivalent cycle service levels with less inventories at product maturity and EOL phases. Auweraer et al. studied multiple sources of installed base information and their influence on spare part demand forecasts and inventory management [21].

When compared to the amount of available literature incorporating time series forecasting techniques in spare parts forecasting, studies on installed base forecasting are fairly limited. This gap in literature has been highlighted by [4] and [6] also highlights the importance of using installed base information to derive more accurate forecasts and enhance current forecasting methodologies. Opportunity for developing new methodologies for spare parts forecasting that incorporate contextual information and align more closely with industry practices currently exists [22]. Moreover, the empirical study by [23] identify a substantial gap in the exploration of integrating planning and forecasting models that specifically address the nuances introduced by the installed base context. The necessity for research is further highlighted by the assessment of the limits of present forecasting systems that disregard the comprehensive contextual data from installed bases. To overcome these drawbacks, there is a clear indication from the literature that further research should study comprehensive models that account for contextual information relevant to the installed base.

2.3. Aircraft component demand forecasting

Aircraft components demand forecasting is unique from general spare part forecasting due to the significant impact of failure on aircraft safety and airworthiness. A single component failure can lead to AOG situations, flight schedule disruptions, and significant financial losses for airlines. Accurate demand forecasting is crucial to ensure components are available when needed, reducing downtime and operational safety [15]. Furthermore, aircraft components are significantly far more expensive than regular spare parts, substantially emphasizing the need of accurate, exact forecasts [24]. The aviation industry is heavily regulated by agencies like FAA, EASA, and Civil Aviation Authority, requiring strict maintenance requirements, quality assurance, and part traceability. Demand forecasting must consider these regulatory requirements to ensure compliance. Additionally, aircraft components have long lead times for sourcing and production, necessitating long term forecasts to accommodate these lead times and avoid critical stockouts [24].

The literature on aircraft component demand forecasting includes various approaches, from standard time series techniques to more complex contextual and hybrid models. Early studies focused on scenario based methods to enhance knowledge and sensitivity in European aircraft manufacturers' forecasting. Traditional time series methods like SES, ARIMA, and Croston are also studied. Studies like [24] use historical demand data patterns to forecast future requirements. Ghobbar et al. introduced a predictive error model for forecasting evaluation [25].

The latest developments in literature often utilize machine learning approaches such as Vector Machines (SVMs), Random Forests, and Artificial Neural Networks (ANNs) for aviation component demand forecasting. Kozik et al. proposed an ANN based model for forecasting the number of spare parts for an aircraft engine [26]. In addition, Grey model also has been applied to aircraft spare parts demand forecasting and it is underlined that this method is beneficial in settings with inadequate historical demand data. Panel data model which integrates time series approaches and cross sectional regression methods, gives the ability to handle specific airline characteristics in demand forecasting. Şahin et al. employed parametric time series methods and ANNs – specifically Multilayer Perceptron (MLP), Recurrent Neural Network (RNN), Time-Delay Neural Network (TDNN), and Radial Basis Function (RBF) models – to forecast spare parts demand for an aviation company [27]. Amirkolaii et al. investigated demand forecasting accuracy in business aircraft spare parts by comparing ANN models with the most frequently used and best-performing forecasting methods for uncertain and unpredictable demand, including Croston, SBA, TSB, and Croston SBJ

(Shale–Boylan–Johnston), as well as classical methods such as Moving Average (MA) and SES [28]. Ekin focused on the analysis of critical aircraft components from an aviation maintenance and repair organization, employing Croston's method, the Syntetos–Boylan approach, and single exponential smoothing (SES). In this study, no ANN models were investigated [29]. The paper presents the development and implementation of an advanced analytics framework at Bombardier Aerospace aimed at improving the aftermarket demand forecasting process [30]. The authors integrate machine learning (ML) models with traditional time series methods within a unified framework. Shafi et al. developed an ANN-based network to forecast demand for aviation service parts exhibiting lumpy patterns, using data procured from the Central Aviation Spares Depot [31].The proposed model was compared, inter alia, with RNN, Croston, SES, and SVM methods. Zhang et al. compare Croston's method, the SBA, feedforward neural networks (FNN), RNN, the long short-term memory (LSTM) model, and Transformer – a newly developed deep learning method – for intermittent demand forecasting using data from a U.S.-based airline service parts provider [32]. Zuvieta et al. provide a recent literature review of 26 articles from 2012 to 2023, discussing time series forecasting methods – both classical statistical approaches (e.g., Croston method, SES) and machine learning models – indicating that while traditional methods are still popular due to their simplicity and interpretability, ML models can provide higher forecast accuracy and support inventory optimization in aviation [33].

When considering contextual forecasting methods in aircraft component demand forecasting, there are numerous research where time series forecasting methods are compared against same with judgmental adjustments [24]. They emphasize the fact that judgement based approach improves the accuracy of forecasts and is critical in defining the proper model that aligns with industry specific constrains and uncertainties. Considering installed base forecasting in aircraft component forecasting, Ghobbar and Friend's study reveals a link between lumpiness in demand and installed base information of aircraft spare parts [25]. They use a generic linear model and airline operator data to identify maintenance and operational data as key drivers of lumpiness in component demand. However, their method is not benchmarked against well-known spare parts demand forecasting methods, which are more general and not tailored to aircraft maintenance and component replacement challenges. Since then, there are no studies dedicated to installed base forecasting of aircraft components.

A literature review indicates that research on spare parts demand forecasting is developing in three main streams: (1) a time series approach, focused on historical demand data; (2) a context-based approach, including installed base forecasting, which incorporates information about the operating population of aircraft; and (3) models based on artificial intelligence (AI). In the aviation field, research comparing classical methods such as Croston, SBA, and SES with machine learning models, including neural networks, predominates. However, the analysis indicates that these models almost exclusively utilize historical demand data, without formally integrating variables describing the structure and condition of the installed base. At the same time, the literature on installed base forecasting, presented in Section 2.2, emphasizes the importance of factors such as fleet size, the number of components per aircraft, reliability, maintenance policies, and operating conditions as key determinants of spare parts demand generation. However, these studies primarily focus on simulation models, regression models, or extensions of exponential smoothing methods, rather than utilizing nonlinear machine learning models.

The analysis presented in Table 1 and the literature review in Section 2.2 clearly demonstrate that existing aviation research uses either neural network models without using information about the installed base [26] or context-based approaches without implementing neural networks [6,19–21]. To the best of our knowledge, none of the reviewed studies explicitly integrate artificial neural networks with installed base-based contextual variables for aircraft component demand forecasting. Hence, there appears to be a gap in literature specifically addressed to this topic. Therefore, this research is aimed at catering to this specific need.

Based on the identified research gap, bearing in mind that the forecasting accuracy of existing methods designed for irregular demand patterns remains limited [28], the main objective of this study was defined as the development and empirical validation of a demand forecasting model for aviation components that integrates installed base-related contextual information with a non-linear artificial neural network architecture in order to overcome the limitations of traditional intermittent demand forecasting methods.

Table 1. Summary of Literature on Aircraft Component Demand Forecasting.

Domain / Data	Uses Neural Network model?	Uses installed base information?	Source
Forecasting the number of spare parts for an aircraft engine (WSK „PZL-Rzeszów” S.A. - currently Pratt & Whitney Rzeszów S.A. , Poland)	Yes	No	[26]
Aviation spare parts demand (Turkish Aircraft Maintenance Repair & Overhaul company)	Yes	No	[27]
Business aircraft spare parts (Dassault Aviation company)	Yes	No	[28]
Demand forecasting for critical aircraft components used in the inventory of a maintenance-repair organization in the aviation sector	No	No	[29]
Aftermarket demand forecasting (Bombardier Aerospace)	No	No	[30]
Demand forecasting for aviation service parts (Central Aviation Spares Depo)	Yes	No	[31]
Intermittent demand forecasting (airline service parts provider/distributor located in the U.S.)	Yes	No	[32]
Literature review	n/a	n/a	[33]

The selection of an ANN was not merely an empirical decision but was grounded in theoretical considerations. The relationships between reliability, flying hours, fleet size, maintenance policy, and component type are inherently non-linear in nature. Moreover, the interactions among these contextual variables are difficult to capture using linear modeling approaches. ANNs enable the modeling of complex, multidimensional relationships without the need to specify an a priori functional form of the model. Therefore, ANN should not be viewed as a simple alternative to existing approaches, but rather as a natural extension of installed base forecasting toward modeling complex causal relationships. What is more, Amirkolaii et al. underline that neural networks model can improve the accuracy of intermittent demand forecasting [28].

3. Methodology

The diagram illustrating the research methodology is presented in Fig. 1. Initially, an extensive literature analysis (Step 1) will be conducted to determine the contextual factors that impact the installed base forecasting of spare parts.

Next, comprehensive data collection (Step 2) will be conducted over a six-year period, focusing on each identified contextual element. Following the initial literature-based study, the Delphi technique (Step 3) will be applied to assess the relevance and applicability of the identified characteristics to aircraft components. Expert feedback and results obtained through the Delphi technique will then be systematically examined using factor analysis (Step 4) to develop the final list of contextual factors related to installed base forecasting of aircraft components.

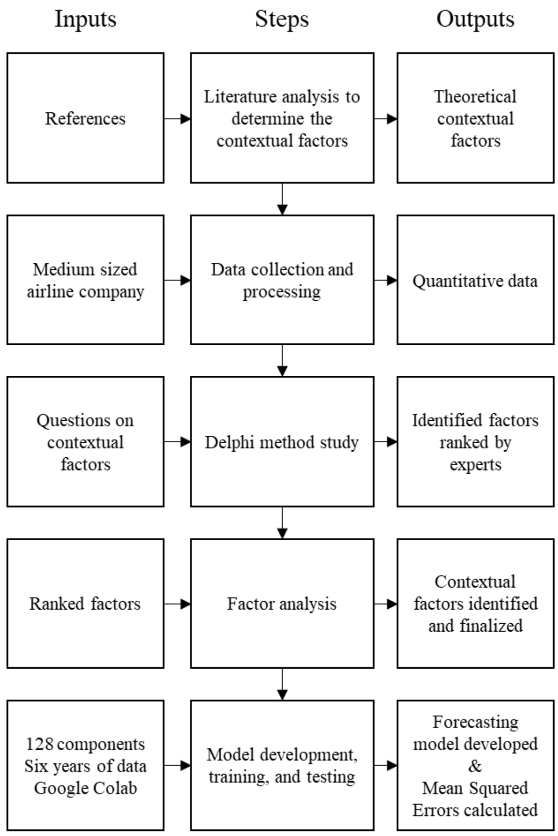

Figure 1. Diagram illustrating the research methodology.

The large dataset collected in Step 2 will be methodically organized and thoroughly analyzed to ensure robustness for subsequent analyses and the development of the forecasting model (Step 5). The dataset will then be divided into two independent subsets: one for training and the other for testing the forecasting model. This approach enables a rigorous evaluation of the model’s forecasting accuracy.

Finally, the forecasting model developed in this study will be benchmarked against traditional spare parts forecasting approaches to assess its effectiveness and relative performance. Overall, this research aims to enhance forecasting accuracy and improve operational efficiency in demand forecasting within airlines’ engineering supply chains. The methodology described in this section and illustrated in Fig. 1 is designed to operationalize and achieve the main research objective defined in Section 2, namely the development and empirical validation of a demand forecasting model for aviation components that integrates installed base-related contextual information with a non-linear artificial neural network architecture to overcome the limitations of traditional intermittent demand forecasting methods.

3.1. Review of contextual factors

For the literature review, a comprehensive search was conducted using online scientific databases using keywords such as ‘spare parts forecasting’ ,‘installed base forecasting’, ‘installed base information’ and ‘contextual factors in forecasting’. In the literature review, only journal articles from Q1 ranked scientific journals were included.

From the comprehensive review of the literature, six key contextual factors were identified as significant in forecasting. These factors are critical in understanding and predicting the behavior of spare parts and installed bases. The factors include number of machines, quantity per machine, age of machines, age of components, part failure probability, environmental and operational conditions (Table 2).

Table 2. Sources of Contextual Factors.

Contextual Factors	Papers
Number of Machines	[21], [34], [35], [36], [37]
Quantity per Machine / Number of Parts	[6], [38]
Age of Machines	[6], [21], [35], [36], [37]
Age of Components	[6], [21], [39], [40]
Part Failure Probability / Reliability	[6], [36], [41], [42], [43]
Maintenance Policy	[6], [20], [34], [36], [37], [40], [44], [45], [46]
Environmental and Operational Conditions	[6], [15], [47]

3.2. Data collection and processing

This study partnered with a medium sized Sri Lankan airline to collect data for a demand forecasting model. The data collection process involved obtaining both quantitative and qualitative data related to factors influencing component demand. Quantitative data was primarily collected from maintenance records retrieved through the ERP system and flight operations data while qualitative data was collected from discussions with engineering maintenance professionals and management.

The data processing phase involves cleaning and transforming the acquired data to ensure high quality of data which accurately represents real world conditions. This extensive data preparation is crucial for improving the overall accuracy of the forecasting model.

3.3. Delphi method

It is needed to identify whether the above identified contextual factors from spare parts forecasting literature are applicable to the subset of aircraft components. Although there are numerous methods for this purpose, Delphi technique presents numerous advantages over the other methods. It utilizes expert consensus via a series of questionnaires and the subsequent iterative rounds of revision, thus granting the ability to refine the ideas over time. This cyclic process is crucial for an aviation industry environment to tackle the technical difficulties associated with the aircraft components. Furthermore, the Delphi method is used to guarantee anonymity, so it cannot be influenced by dominant personalities, which is especially critical in a sector like aviation.

A questionnaire was prepared to conduct this Delphi method study. There, the experts were asked to rate the identified factors on a scale of 1 to 5 (1 being not important, 5 being extremely important), on the importance of each of the factors in forecasting aircraft component demand. The questionnaire was presented to eight experts from the engineering materials and component management section of an airline based in Sri Lanka. Two successful iterative rounds of revisions were conducted.

3.4. Factor analysis

After the first round of Delphi method, collected ratings were subjected to analysis. There are multiple statistical parameters to analyze the results including average, weighted average, mode, median and range.

The experts participated in this survey are highly experienced in the aviation industry with 157 years of total experience in the industry which is average 19.625 years of experience per expert. Hence, for this particular dataset Weighted Average based on years of experience of the experts in the aviation industry was considered as the parameter for first round data analysis. The analysis results, along with comments from the initial round, were presented to the experts for iteration, ensuring the anonymity of the ratings and feedback from the first round. The process was once again repeated and then the contextual factors related to installed base forecasting of aircraft components were identified and finalized.

3.5. Forecasting model development

A forecasting model was developed using Google Colab, a Python based environment. Six years of data were split into training and testing sets, with 66.67% training data and 33.33% testing data. The model was designed using Artificial Neural Networks (ANNs) and trained using features and historic demand data. The model uses contextual factors as features with a median strategy to predict demand based on the relationship established through the model. Neural network structure is composed by dense layers with ReLU function as the activation function. These are typical of a regression problem. This model is trained with the help of the Adam optimizer and with the goal of minimizing the mean squared error loss between predicted value and actual demand.

The ANN (Fig. 2) architecture consists of an input layer with 8 neurons corresponding to the number of contextual features, followed by 2 hidden layers with 64, 32 neurons respectively, each employing the ReLU activation function to introduce non-linearity and enable the model to capture complex demand patterns. The output layer contains a single neuron with a linear activation function to produce continuous demand predictions suitable for the regression task. The model was trained using the Adam optimizer with a learning rate of 0.001, beta parameters β_1= 0.9 and β_2=0.999, and a batch size of 32 samples. Training was conducted over 150 epochs with an early stopping mechanism monitoring validation loss with a patience of 20 epochs to prevent overfitting. The training dataset was further split into 80% for actual training and 20% for validation to tune hyperparameters and monitor model convergence. Model performance during training was tracked using training and validation MSE curves, and the weights corresponding to the minimum validation loss were retained as the final model. To ensure robustness, k-fold cross-validation was performed, and the model's generalization capability was assessed on the unseen testing set representing the remaining 33.33% of the data.

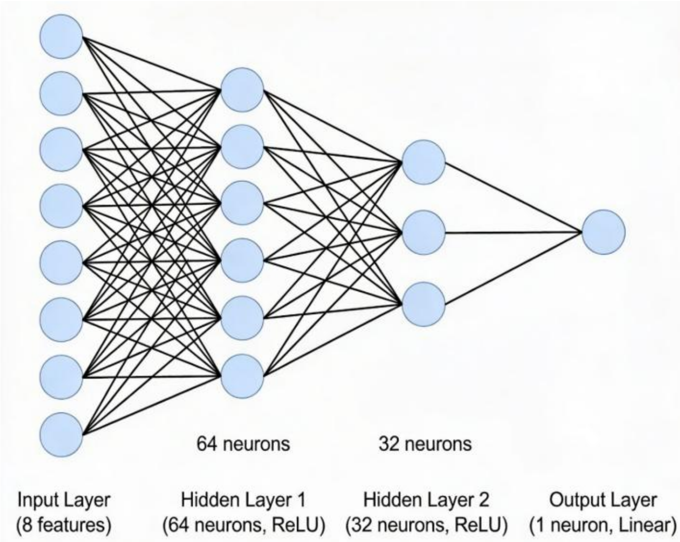

Figure 2. Architecture of the developed ANN.

The data were divided into 5 categories based on the factor ‘component type’ namely, ‘electrical system, avionics and instruments’, ‘fuel system and powerplant’, ‘hydraulics system’, ‘structure and landing gear’ and ‘cabin, cockpit and safety items’. 128 components were chosen to represent the above 5 categories and to best represent repairable and rotable components in the aircraft.

The model's performance is evaluated using the Mean Squared Error (MSE) between the predicted and actual demand and also benchmarked against the well established Croston’s method that is famous for intermittent demand forecasting. Croston’s method is selected as the primary benchmark due to its longstanding use and acceptance in industry for handling intermittent and highly variable demand patterns, making it a natural point of comparison for evaluating improvements offered by machine learning based models. However, it is worth noting that the Syntetos–Boylan Approximation, a modified version of Croston’s method, is frequently reported to provide slightly better accuracy by correcting Croston’s inherent bias. Including a comparison with SBA in addition to Croston’s method could therefore strengthen the analysis and provide a more comprehensive evaluation of the model's performance. Nevertheless, the results obtained by Amirkolaii et al. indicate that Croston-based methods achieve a comparable forecasting accuracy [28]. For this reason, the authors decided to compare the newly proposed approach – combining ANN with installed base forecasting – primarily with the classical Croston method, as it is expected that SBA and other modifications of Croston would yield similar levels of accuracy.

4. Results and analysis

4.1. Delphi method results analysis

The first round of the study identified the size of the fleet as a crucial factor, with a consensus level of 100%. The quantity per aircraft was also highly rated, with experts indicating its direct correlation to component demand. The age of aircrafts had minimal impact on component demand, while the age of components was not a demand driver. Reliability of components was a top priority and maintenance, and repair practices were highly rated, with a consensus level of 100%. Environmental and operational conditions were also considered, with flying hours being the most critical and appropriate quantitative factor. Component type was not initially included in the Delphi method questionnaire but was later discussed in subsequent rounds. Its importance was underlined, as different components have unique characteristics, and it was agreed with 87.5% consensus level to be a contextual factor in aircraft component demand forecasting.

In conclusion, the Delphi method identified several factors that should be considered when using installed base forecasting for aircraft components. These factors include the size of the fleet, quantity per aircraft, reliability of components, maintenance and repair practices, flying hours, and component type.

4.2. Results analysis of the forecasting model

Component Type 1 - Electrical System, Avionics and Instruments shows a MSE of 6.414 in the developed neural network model and a MSE of 12.288 in the Croston model. Therefore, based on the MSE values obtained, the developed neural network model demonstrates superior performance in forecasting in this component category when compared to the Croston's method. The resulting violin plot and comparison of results for Component 1 are presented in Fig. 3 and Fig. 4.

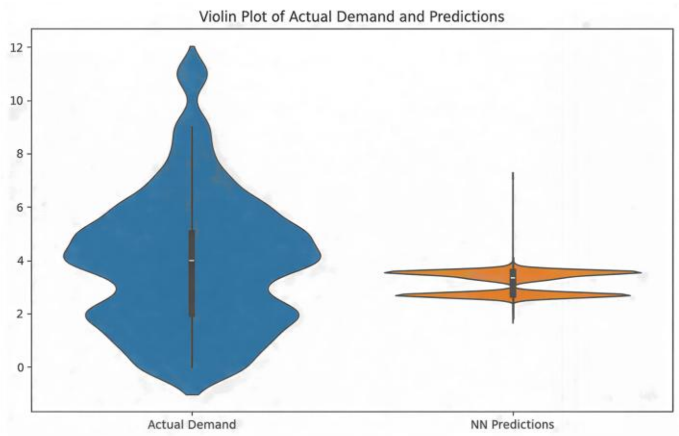

Figure 3. Component Type 1 - Volin Plot.

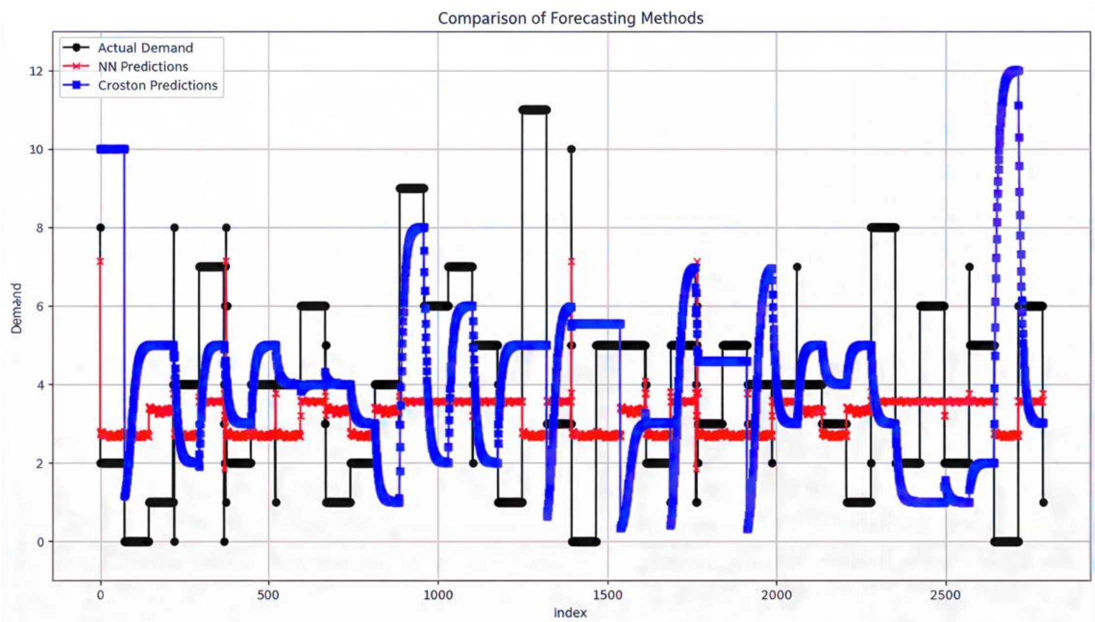

Figure 4. Component Type 1 – Model Comparison.

Component Type 2 – Fuel System and Powerplant shows a MSE of 5.262 in the developed neural network model while the Croston model shows a MSE of 4.607. Croston's method outperforms the developed neural network in this specific scenario. The lower MSE of the Croston method indicates that, in this case, its predictions are closer to the actual values compared to those of the neural network model. This outcome suggests that the dynamics of the data in this particular component category might be better captured by the Croston method. Therefore, despite the neural network's typically superior performance, the Croston method demonstrates effectiveness in this specific forecasting context. Results are illustrated in Fig. 5 and Fig. 6.

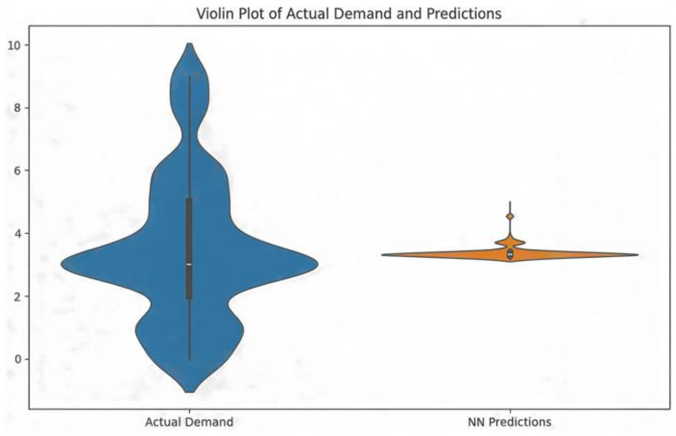

Figure 5. Component 2 - Demand Variation.

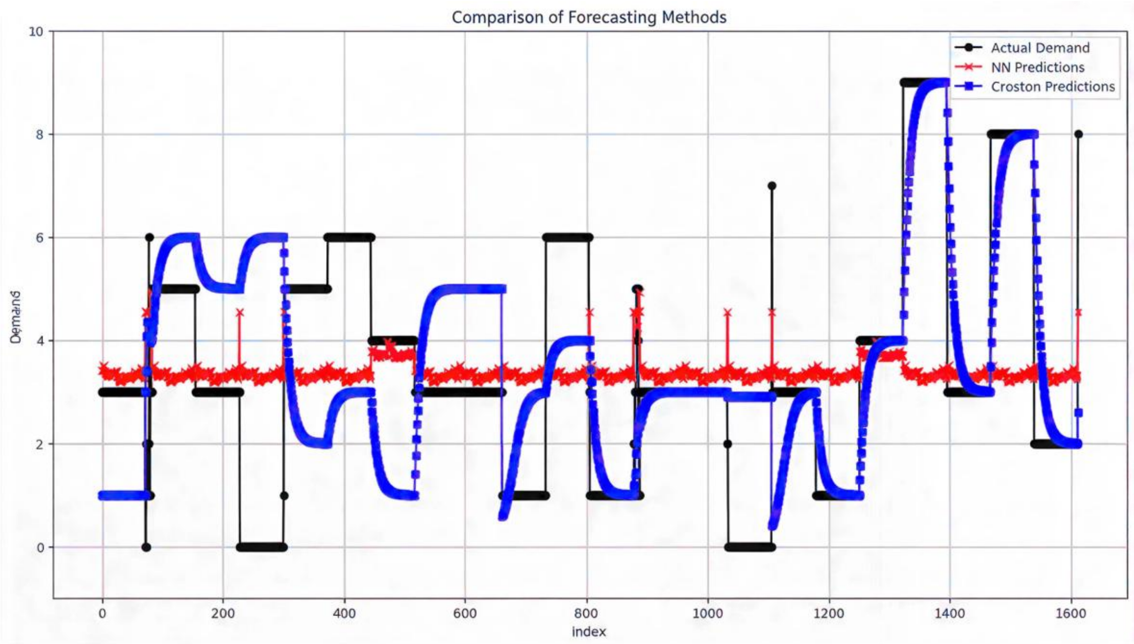

Figure 6. Component Type 2 - Model Comparison.

Component Type 3 – Hydraulic System shows a MSE of 4.908 in the developed neural network model while the Croston model shows a MSE of 6.296. Therefore, based on these MSE values, the neural network model demonstrates superior performance in forecasting compared to the Croston method in this particular analysis for component type 3. Results are depicted in Fig. 7 and Fig. 8.

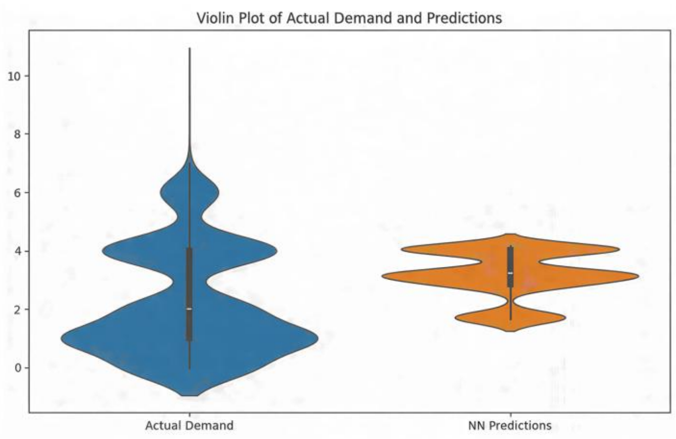

Figure 7. Component Type 3 - Demand Variation.

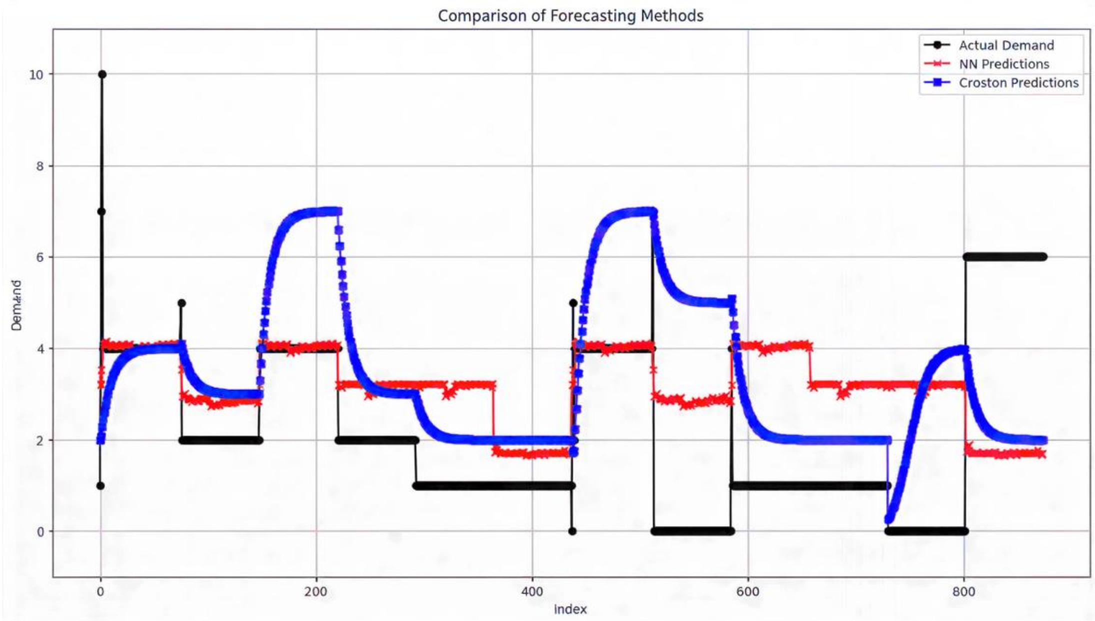

Figure 8. Component Type 3 - Model Comparison.

Component Type 4 – Structure and Landing Gear shows a MSE of 5.987 in the developed neural network and MSE of 7.573 in Croston model. This suggests that the neural network's predictions are more aligned with the actual values than those generated by the Croston method. Hence, in this particular analysis, the neural network model demonstrates superior forecasting performance over the Croston method. Results are illustrated in Fig. 9 and Fig. 10.

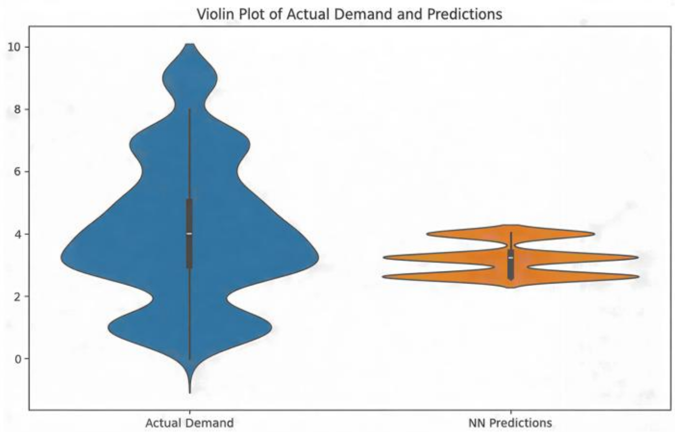

Figure 9. Component Type 4 - Demand Variation.

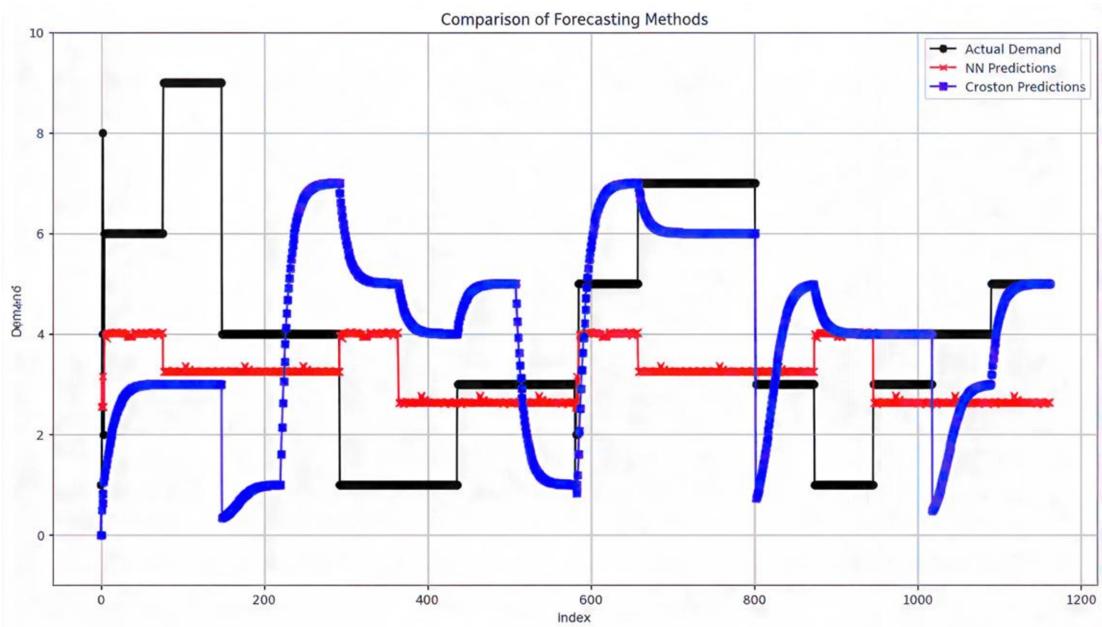

Figure 10. Component Type 4 - Model Comparison.

Component Type 5 – Cabin, Cockpit and Safety Items show a MSE of 5.919 in the developed neural network and MSE of 9.449 in the Croston model. This implies that the neural network's predictions align more closely with the actual values compared to those generated by the Croston method. Therefore, in this particular evaluation, the neural network model exhibits superior forecasting performance over the Croston method. The results are presented in Fig. 11 and Fig. 12.

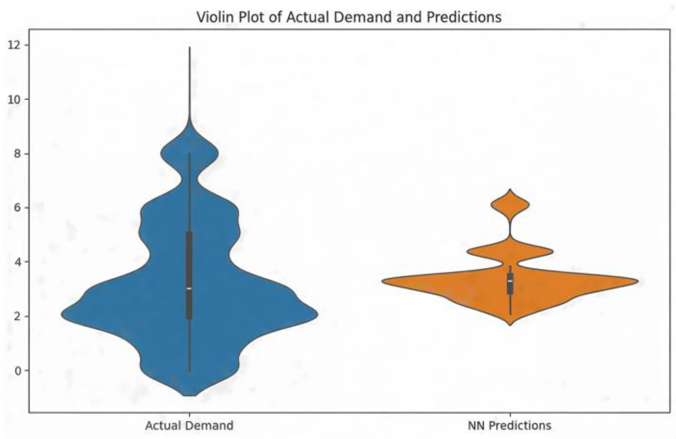

Figure 11. Component Type 5 - Demand Variation.

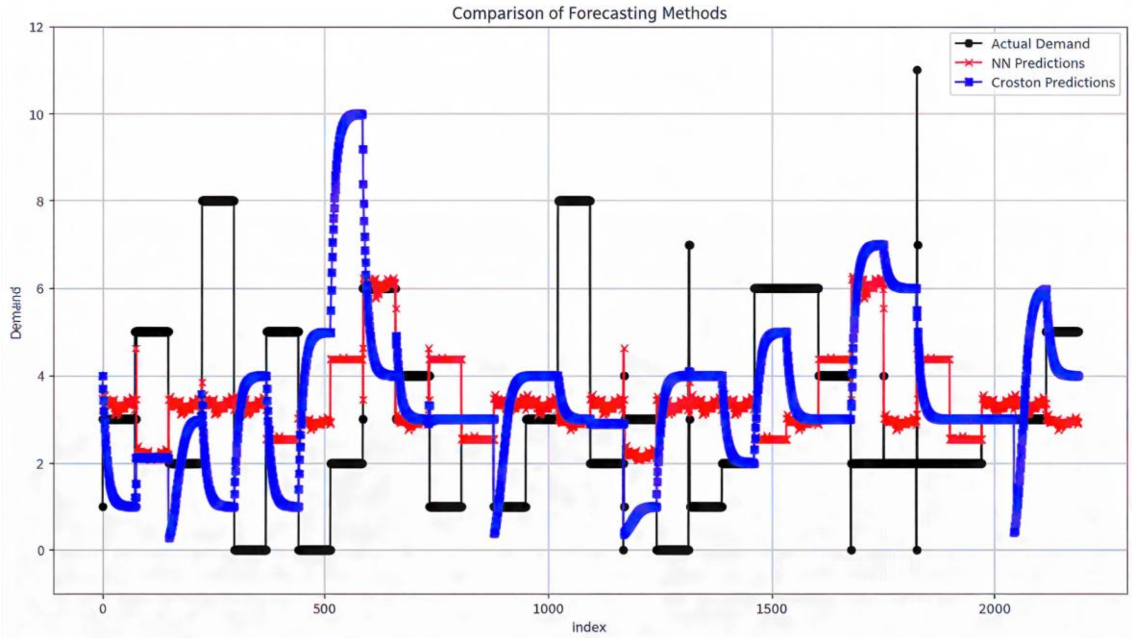

Figure 12. Component Type 5 - Model Comparison.

5. Discussion

5.1. Contextual factors identified through delphi method

Delphi method in this research provided the opportunity to understand the contextual factors that may affect the installed base forecasting of aircraft components. Available literature on installed base forecasting of spare parts focuses on the general contextual factors influencing the demand for spare parts, however, it fails to analyze the industry specific factors. This study has shown a unique methodology that integrates industry specific and circumstantial factors. Through the participation of the expert consensus and continuous refinement, the Delphi method finally provided a multi-dimensional understanding of the specific issues and decision points associated with the demand forecasting in aviation.

Moreover, iterative nature of the Delphi method allowed to introduce 'component type' a new contextual factor that has not been found in the sources of IBI in current installed base forecasting of spare parts research studies. Hence, Delphi method offered a nuanced understanding of the unique considerations inherent in forecasting component demand within the aviation industry.

Although, age of machines and age of components were considered as a pivotal contextual factor related to the size and status of the installed base in studies like [6] and [21], this Delphi study highlighted that they are not applicable for forecasting of aircraft components. For instance, research indicates that factors such as the design service objectives and the Limit of Validity (LOV) are more pertinent than merely the age of the aircraft when setting maintenance and forecasting requirements [24]. Furthermore, component replacement and reequipment cycles in aviation, including MRO operations, often render the age of individual components since these parts are regularly replaced or refurbished [25]. This reequipment cycle ensures components remain up to date irrespective of the component's overall age.

Overall, Delphi method offered a unique and effective approach to identifying contextual factors for forecasting aircraft component demand.

5.2. Proposed forecasting model

The novelty of this study lies in the integration of contextual variables describing the installed base with an ANN architecture and the empirical validation of this approach in a real-world airline operating environment. Furthermore, unlike previous studies [26–33], the identification of aviation-specific contextual factors - including the "component type" variable - was conducted using the Delphi method, which allowed us to link the theory of sporadic demand forecasting with reliability theory and the concept of maintenance-driven demand generation. As a result, the proposed solution is neither a classical time series model, nor a simulation model of the installed base, nor merely a comparison of ANN with Croston's method. Instead, it is a causal forecasting model that uses ANN to estimate demand generated by a population of operating components. Our study constitutes an attempt to address the theoretical challenge of integrating the demand generation mechanism embedded in installed base dynamics with a non-linear ANN-based modeling framework capable of capturing complex interactions among contextual variables.

In development of the forecasting model the following factor was taken into consideration. In aircraft maintenance, preventive maintenance policy is used for majority of the components. It is time or operating conditions-based policy, and the component will be replaced regardless of its condition within a specific interval. Even though, a component failure can still occur between two preventive replacements calling for corrective maintenance task. In this research, both preventive and corrective maintenance actions are assumed to replace failed or worn parts. Similar assumption is considered by [6] when developing their forecasting model. When considering the components for the analysis only components with preventive maintenance policy were used otherwise a conflict of the variables can occur. Hence although identified as a source of IBI, maintenance and repair practices were kept has a constant when developing the forecasting model.

As a consequence, of assuming preventive replacements as replacement of failed components, the contextual factor of reliability of components was incorporated to the forecasting model through historic component replacement data.

All the other identified contextual factors in the previous step; fleet size, quantity per aircraft, flying hours and component type were directly integrated to the model as features.

Developed model, which is based on Neural Networks, showed that it has a superb performance in predicting intermittent demand for aircraft components in several component categories compared to the traditional Croston method. As shown in Fig. 13, low MSE values for the neural network model suggest that the model predicts values which are close to the actual value, improving forecasting accuracy. Nevertheless, it is noteworthy that the developed forecasting model performance differed across the component types, with instances where the Croston method was superior to the neural network. This variability, therefore, calls for customized forecasting techniques that are contingent on the shared attributes of component data.

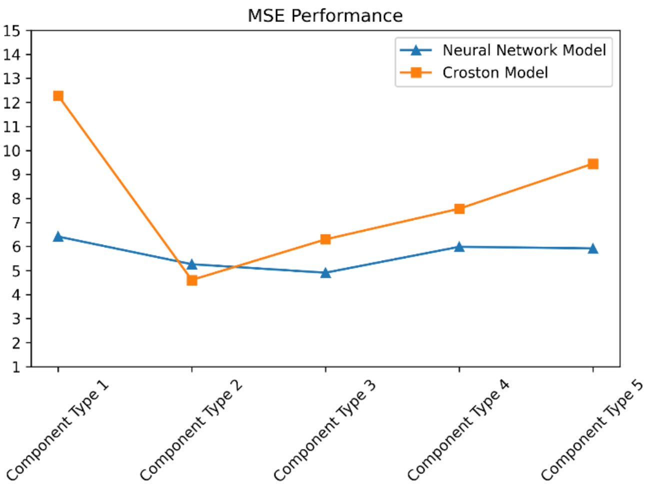

Figure 13. MSE Performance of Models.

When further analyzing the performance of the developed model, it is highlighted that the model performs better in the component categories of ‘electrical system, avionics and instruments’, ‘hydraulic system’, ‘structure and landing gear’ and ‘cabin, cockpit and safety system’ than the traditional

Croston method. However, in the component category of 'fuel systems and power plant', Croston method outperforms the developed neural network model. Even though, the difference between the MSE of the two methods is not a very significant amount. Hence, it can be concluded that the developed model performs better in forecasting intermittent demand of aircraft components. In addition, variability in forecasting performance across different component types underscores the importance of tailored approaches to spare parts demand forecasting.

6. Conclusion

The originality of this study stems from the integration of contextual variables describing the installed base with an ANN architecture, combined with empirical validation of this methodology in a real-world airline operating environment. Unlike previous studies, aviation-specific contextual determinants were systematically identified using the Delphi method, enabling a conceptual link between sporadic demand forecasting and reliability theory and the concept of demand generation resulting from maintenance processes. Consequently, the proposed approach is neither a classical time series model nor a simulation model of the installed base, nor a mere comparison of the ANN with Croston's method. Instead, it is a causal forecasting framework using ANN to estimate demand resulting from the dynamics of the population of operational aircraft components.

The Delphi method enabled the identification of contextual factors specific to the aviation sector, crucial for forecasting accuracy. Unlike studies focusing on general contextual variables, this study takes into account industry-specific conditions, deepening our understanding of demand generation mechanisms in aviation. The iterative nature of the Delphi method also allowed for the introduction of new variables, such as "component type," which have not previously been explicitly addressed in installed base forecasting studies. Furthermore, the study results indicate that in aviation environments, factors such as design durability goals and maintenance cycles may play a more significant role than component age alone, complementing existing literature assumptions.

The developed neural network-based forecasting model demonstrated superior performance in this case study compared to traditional methods such as the Croston method. Incorporating contextual variables, including reliability parameters and historical replacement data, contributed to reducing forecast errors in intermittent demand conditions. However, it should be emphasized that model performance varied depending on the component category, indicating the need for further adaptation of forecasting approaches to the specific data characteristics of individual component groups. The study results therefore provide preliminary confirmation that integrating installed base information with ANN architecture can improve forecast accuracy and reduce operational risk in engineering supply chains.

The presented results are based on data from a single airline operating within a specific operational and regulatory context, which limits the generalizability of the results to other organizations or sectors. Therefore, further research should include validation of the model in other airlines and under different operational conditions to assess its robustness and applicability.

In the future, it also seems worthwhile to develop an implementation framework enabling the practical implementation of the proposed approach in the airline industry, including an analysis of the potential for integrating the forecasting model with ERP systems used by airlines. Further research could also focus on assessing the transferability of the proposed solutions to other sectors with similar reliability and maintenance structures, such as rail transport, the defense industry, or underground mining [48].

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