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A Proposed Demand Forecasting Method for Aircraft Maintenance Spare Parts in Aircraft Maintenance Operations: A Case Study

Pramote Chaiman, Woramol C. Watanabe*

Faculty of Logistics and Digital Supply Chain, Naresuan University, Mueang, Phitsanulok, 65000

*Corresponding author E-mail: woramolc@nu.ac.th

Abstract

This study aims to analyze the demand patterns of aircraft spare parts used in unscheduled maintenance and to propose appropriate forecasting methods tailored to each demand type. Historical usage data spanning five years (2018 to 2022) were collected for 58 distinct spare parts. The demand classification was conducted using two key indicators, namely the Average Demand Interval (ADI) and the Squared Coefficient of Variation (CV^2), which facilitated the categorization into Smooth, Intermittent, Erratic, and Lumpy demand patterns. Following the classification, suitable forecasting techniques were applied to each demand type. Exponential Smoothing was used for Smooth demand, the Bootstrap Method was applied to Intermittent demand, and Croston's Method was adopted for both Erratic and Lumpy demand. Forecast accuracy was assessed by comparing the Mean Squared Error (MSE) of each technique with the conventional Moving Average method currently in use. The results indicate that the majority of the spare parts, accounting for 65.52 percent, exhibit an Intermittent demand pattern. The proposed pattern-specific forecasting techniques demonstrated notable improvements in accuracy: for the dominant Intermittent group, the Bootstrap Method reduced forecast error (MSE) by approximately 42.61%; Exponential Smoothing reduced MSE for Smooth demand by 15.91%, and Croston's Method yielded an 11.75% improvement for Erratic demand. However, accuracy for the Lumpy item declined due to model limitations. Overall, this tailored approach led to an average forecast error reduction of 18.37% across all items compared to the conventional Moving Average method. These findings emphasize the importance of aligning forecasting techniques with actual demand characteristics to improve prediction accuracy. The proposed approach improves inventory decision-making in aircraft maintenance operations and shows potential for broader application in industries facing similar demand irregularities.

Keywords: Demand Forecasting, Intermittent Demand, Spare Parts, Inventory Management, Bootstrap Method, Aviation Maintenance, MRO

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1. INTRODUCTION

Demand forecasting is a critical process in inventory management and resource planning across industries, encompassing manufacturing, transportation, and service sectors. Accurate forecasting enables organizations to procure raw materials and schedule production efficiently, thereby reducing excess inventory costs and minimizing stockouts that could delay responses to customer demand. As such, demand forecasting plays a vital role in enhancing long-term operational efficiency and competitiveness.

Various forecasting techniques have been developed to address different demand characteristics. A thorough understanding of demand patterns allows organizations to apply forecasting methods that are most appropriate for each situation, ultimately improving accuracy and optimizing inventory management.

In the aviation industry, forecasting the demand for spare parts used in aircraft maintenance is of paramount importance. Maintenance activities frequently encounter irregular and highly volatile demand for parts. Inaccurate forecasting can lead to spare part shortages during critical maintenance periods or, conversely, to excessive stockpiling, resulting in unnecessary inventory costs. A case study conducted within an aircraft maintenance unit revealed that reliance on a single forecasting technique, specifically the Moving Average method, has led to operational challenges. In some cases, forecast inaccuracy caused delays in maintenance due to unavailable parts, which disrupted the unit's operational plans and resulted in additional costs related to urgent procurement or idle time. In other cases, excessive inventory led to increased holding costs, including storage expenses, part degradation, and opportunity costs due to capital being tied up in surplus inventory.

Achieving an optimal balance between spare part availability and inventory cost is essential for the aviation sector. Efficient spare parts inventory management directly supports safety, service reliability, and cost control. Consequently, aviation organizations must recognize the importance of demand forecasting and continuously refine forecasting techniques to reflect the volatility and diversity of real-world demand. This study aims to address these challenges by analyzing the historical usage data of high-value aircraft spare parts to classify their demand patterns and by proposing suitable forecasting techniques that align with those patterns. It is hypothesized that applying forecasting methods tailored to specific demand characteristics will improve prediction accuracy, reduce the incidence of spare part shortages, and enhance inventory management efficiency in aircraft maintenance operations.

2. LITERATURE REVIEW

2.1 Classification of Aircraft Spare Parts

In the aviation industry, effective management of aircraft spare parts and components is crucial because it directly affects maintenance readiness and flight safety. According to the International Air Transport Association (IATA, 2015), aircraft spare parts can be grouped into three main categories. The first group consists of Rotables, which are high-value components such as engines that can be repeatedly used and restored to serviceable condition after failure through repair or maintenance. The second group includes Repairables, which are lower-value items like oxygen cylinders that can also be repaired, although they typically have higher failure rates and shorter service lives compared to rotables. The third group is Consumables, which are non-repairable parts used only once and then discarded, such as fasteners and gaskets. This classification is key for determining inventory strategies and forecasting requirements, as it identifies parts needing frequent replenishment to ensure safe aircraft operations.

2.2 Classification of Demand Patterns

Understanding demand patterns is fundamental to effective inventory control and accurate forecasting, particularly in the aviation maintenance context. Thummathid (2020) proposed a widely recognized classification framework that categorizes demand into four distinct types, each defined by the frequency and volume of part usage. To facilitate this classification, two statistical indicators are commonly employed: the Average Demand Interval (ADI), which measures the average time between non-zero demand occurrences, and the Squared Coefficient of Variation (CV^2), which captures the relative variability in demand magnitude. These metrics are calculated from historical usage data and enable the systematic identification of demand characteristics across different spare parts.

The four demand types include Smooth Demand, which refers to consistently recurring demand with low variability; Intermittent Demand, characterized by irregular demand intervals that complicate prediction; Erratic Demand, marked by sharp and unpredictable fluctuations; and Lumpy Demand, which involves sporadic demand occurrences combined with large order quantities. Aircraft spare parts may exhibit any of these demand behaviors depending on their operational role and maintenance cycle. Therefore, accurate demand classification is essential prior to selecting forecasting techniques, as mismatches between demand type and forecasting method can lead to significant inefficiencies such as overstocking, part shortages, and increased holding costs.

2.3 Demand Forecasting

Demand forecasting plays a pivotal role in inventory management, enabling organizations to plan proactively and respond efficiently to customer needs. Accurate forecasting minimizes the risk of overstocking, which incurs unnecessary storage costs, while also mitigating shortages that could disrupt operations. Therefore, demand forecasting improves service readiness and organizational responsiveness to market fluctuations (Watanabe, 2023). Fundamentally, demand forecasting methods can be classified into three main categories. The first is the Causal or Regression Method, which employs mathematical modeling to examine the relationship between demand and external variables such as economic conditions and seasonal factors. This approach allows organizations to quantify how such factors influence demand patterns. The second is the Qualitative Method, which relies on expert judgment and is particularly useful when historical data are unavailable, or uncertainty is high. It is commonly applied to forecast new products or services with no prior demand history. The third is the Time Series Method, which utilizes historical data to project future demand by identifying patterns such as trends, seasonality, and random fluctuations. Each method has its own strengths and is selected based on the nature of the data, the forecasting context, and the decision-making needs of the organization.

Due to the irregular demand for aircraft spare parts, selecting a forecasting technique that matches each item's specific demand pattern is essential for accuracy. To address this, the present study adopts four forecasting techniques, each matched to a corresponding demand type.

1. Moving Average Method

The Moving Average Method is a widely used and straightforward time series forecasting technique. It estimates future demand by averaging past demand values over a specified number of historical periods. This approach assumes that future demand will reflect the average behavior of recent periods, effectively smoothing out short-term fluctuations.

$$\hat{x}_t = \frac{\sum_{i=1}^{n} x_i}{n}$$

where:

$\hat{x}_t$ = Forecasted demand at time *t*

x_i = Actual demand observed at time *i*

n = Number of historical periods used in the calculation

2. Exponential Smoothing Method

The Exponential Smoothing Method improves upon the Moving Average approach by assigning greater weight to more recent observations. This makes it particularly effective for datasets with identifiable trends or short-term variability. Unlike the Moving Average method, which treats all past data equally, Exponential Smoothing places emphasis on the latest demand values, allowing for more responsive and adaptive forecasting.

The forecast for the next period is computed using the following formula (Watanabe, 2023):

$$\hat{x}_{t+1} = \hat{x}_t + \alpha (x_t - \hat{x}_t)$$

where:

$\hat{x}_{t+1}$ = Forecasted demand for time $t+1$

$\hat{x}_t$ = Forecasted demand at time t

x_t = Actual demand observed at time t

α = Smoothing constant (0 - 1)

3. Croston's Method

Croston's Method is a forecasting technique specifically developed to handle irregular demand, which is characterized by sporadic and unpredictable occurrences. Such patterns are commonly found in aircraft maintenance, where spare parts may not be required every period. Traditional methods such as Moving Average or Exponential Smoothing often fail in these cases due to their assumption of continuous demand. In contrast, Croston's Method improves forecast accuracy by independently estimating both the demand size and the interval between non-zero demands (Croston, 1972; Thummathid, 2020; Baisariyev et al., 2021).

This dual-component approach is particularly effective when zero-demand periods are frequent. The forecast for the demand size Yt when actual demand is non-zero is computed using the exponential smoothing formula (Thummathid, 2020):

$$Y_t = \alpha X_{t-1} + (1-\alpha)\, Y_{t-1}$$

where:

Y_t = Estimate mean size of non-zero demand size at time t

X_{t-1} = Actual non-zero demand in the previous demand period

α = Smoothing constant

In addition to forecasting the demand size, Croston's Method also estimates the interval between non-zero demands. The smoothing formula for the inter-demand interval is given as follows (Thummathid, 2020):

$$P_t = \alpha Q_{t-1} + (1 - \alpha)\, P_{t-1}$$

where:

P_t = Estimate means interval between non-zero demand at time t

Q_{t-1} = Actual time interval (in periods) since the last non-zero demand
α = Smoothing constant

After independently forecasting both the demand size (Yt) and the inter-demand interval (Pt) the final demand forecast for a given period is computed as (Thummathid, 2020):

$$Ft = \frac{Y_t}{P_t}$$

where:
F_t = Forecasted demand at time t

4. Bootstrap Method

The Bootstrap Method is a forecasting technique developed to address the challenges of intermittent demand, where traditional time series models often fall short due to frequent zero-demand periods. This method enhances forecasting accuracy by using resampling techniques to generate multiple synthetic datasets that preserve the statistical structure of the original data. These datasets are then used to compute forecast values through statistical aggregation (Bookbinder & Lordahl, 1989;Willemain et al., 2004).

The process begins with random sampling with replacement from the original historical demand dataset $\{x_1, x_2, x_3 \ldots, x_n\}$ (Bookbinder & Lordahl, 1989). Each resampling iteration i produces a new simulated dataset of size n, defined as:

$$xi = \{x_{i1}, x_{i2}, x_{i3} \ldots, x_{in}\}$$

Where each element x_{ij} is randomly drawn from the original dataset:

$$x_{ij} = \in \{x_1, x_2, x_3 \ldots, x_n\}$$

After generating bootstrap samples, each synthetic dataset is passed through a defined forecasting function $f(\cdot)$ to obtain an individual forecast $\hat{\theta}_i$. The overall forecast value $\hat{\theta}^*$ is then obtained by aggregating the forecasts across all bootstrap replications:

$$\hat{\theta}^* = f(x_{i1}, x_{i2}, x_{i3} \ldots, x_{in})$$

This procedure allows the model to reflect uncertainty and variability in intermittent demand by leveraging empirical data patterns rather than relying on strict parametric assumptions.

In the case study under investigation, the organization currently employs only the Moving Average method to forecast demand for all categories of spare parts, regardless of their distinct usage patterns. This generalized approach often leads to inaccuracies, particularly when the demand is irregular or volatile. To address this limitation, the present study proposes a pattern-specific forecasting framework in which forecasting techniques are selected based on the identified demand characteristics of each item. Specifically, Exponential Smoothing is applied to items with Smooth Demand, where demand occurs regularly with low variability. The Bootstrap Method is used for items exhibiting Intermittent Demand, characterized by irregular occurrence and frequent zero-demand periods. Croston's Method is employed for items with Erratic Demand, which show high volatility, as well as for Lumpy Demand, which features sporadic but high-volume usage. By aligning forecasting techniques with specific demand patterns, this approach aims to improve prediction accuracy, enhance spare parts planning, and reduce both shortages and excess inventory in aircraft maintenance operations.

Table 1 Comparison of Forecasting Methods

Forecasting Method	Strengths	Limitations	Key Differences
Moving Average	Simple and easy to calculate.	Slow to react to changes. Unsuitable for intermittent, erratic, or lumpy patterns because it assumes continuous demand.	Averages a fixed window of historical data.
Exponential Smoothing	More responsive than Moving Average by weighting recent data more heavily. Ideal for stable, non-intermittent (Smooth) demand.	Not designed to handle the zero-demand periods characteristic of intermittent, erratic, or lumpy patterns.	Uses a smoothing constant (alpha) to weight all past data exponentially.
Croston's Method	Specifically designed to handle zero-demand periods by separating forecasts for demand size and demand interval. The standard approach for erratic and lumpy demand.	Can be biased and less accurate than specialized bootstrap methods for highly variable intermittent demand.	Deconstructs demand into two separate components: size and occurrence frequency.
Bootstrap Method	Most effective method for intermittent demand. Does not assume an underlying data distribution. Proven to be more accurate than Croston's and Exponential Smoothing for intermittent patterns.	More computationally intensive than other methods. May have limitations with non-stationary data.	A non-parametric, data-driven simulation method that forecasts an entire probability distribution.

2.4 Forecast Accuracy Measurement

Evaluating the accuracy of forecasting methods is essential to ensure that forecasted values closely approximate actual demand. Forecast performance is typically assessed through various statistical techniques that measure both bias, which refers to the tendency of forecasts systematically deviate in one direction, and precision, which indicates the closeness of forecasted values to the actual demand in each period (Watanabe, 2023).

Several well-established metrics are commonly used to evaluate forecast performance. Mean Error (ME) calculates the average difference between forecasted and actual values and serves as a basic indicator of whether forecasts tend to consistently overestimate or underestimate demand. However, ME may be less informative when dealing with volatile data. Mean Absolute Deviation (MAD) addresses this by measuring the average of absolute differences, thereby capturing overall forecast accuracy without regard to error direction. Mean Squared Error (MSE) builds on this by squaring forecast errors before averaging, which gives more weight to larger errors and is particularly useful for highlighting major forecasting inaccuracies. This aligns with the objective of the current study, which seeks to identify clear differences in model performance. Lastly, Mean Absolute Percent Error (MAPE) expresses forecast errors as a percentage of actual demand, making it suitable for comparing models across datasets with different scales. However, MAPE becomes problematic when actual demand values are zero, leading to undefined or distorted results.

Each of these metrics offers different insights depending on the characteristics of the data and the forecasting objectives. This aligns with approaches in previous studies, where metrics such as MSE and MAPE were commonly used to evaluate and compare model performance for intermittent and lumpy demand (Thummathid, 2020; Baisariyev et al., 2021). In this research, Mean Squared Error (MSE) is selected as the primary performance indicator due to its ability to emphasize large deviations and provide a clear evaluation of forecasting error, which is critical for analyzing and comparing the performance of various forecasting methods applied to aircraft spare parts. Furthermore, to formally validate the comparison, statistical tests such as the paired t-test are often employed to confirm if a model's performance is significantly superior to others, a practice demonstrated in recent supply chain forecasting literature. (Jahin et al., 2025).

2.5 Related Studies

Several studies have highlighted the importance of accurate forecasting for aircraft spare parts. Harimansyah and Imaroh (2020) identified inaccurate planning and forecasting as the primary contributors to high inventory levels and demonstrated that appropriate forecasting techniques could significantly reduce forecasting errors. Similarly, the challenge of intermittent demand, which this study found to be the most common pattern, was addressed by Thummathid (2020), who compared Croston's Method, Holt's Linear Method, and a Multi-Layer Perceptron Neural Network, finding the neural network model to be most accurate for such irregular demand patterns. The effectiveness of the Bootstrap Method for intermittent demand, a key technique in our proposed approach, was validated by Baisariyev et al. (2021) who found it offered higher accuracy than traditional methods in managing such demand.

More recent studies have further explored the use of advanced computational methods. For instance, Fan et al. (2023) introduced a method that first uses a clustering algorithm to group spare parts based on their intermittent features before applying a forecasting model, reinforcing the principle that classifying demand patterns is a critical preliminary step. Furthermore, Shafi et al. (2023) focused specifically on the aviation industry, applying a Long Short-Term Memory (LSTM) neural network to tackle lumpy and intermittent demand, demonstrating the potential of deep learning models to improve forecast accuracy and aviation safety.

These studies collectively underscore a clear trend towards adopting more sophisticated, pattern-specific forecasting methods over traditional, one-size-fits-all approaches. To synthesize these findings and position the current research, a summary of key literature is presented in Table 2.

From the literature review summarized in Table 2, a research gap emerges. While previous studies have effectively demonstrated the superiority of specific forecasting methods for certain demand patterns, a comprehensive framework that first classifies demand into multiple patterns (Smooth, Intermittent, Erratic, and Lumpy) and then systematically applies a corresponding, validated forecasting technique to each is less explored in a real-world aviation case study. This study aims to fill that gap by not only identifying the dominant demand patterns in an aircraft maintenance environment but also by empirically comparing a pattern-specific forecasting approach against the conventional, one-size-fits-all Moving Average method.

Table 2 Summary of Key Literature and Research Gaps

Researcher(s) (Year)	Key Method(s) Used	Key Finding(s)	Gap / Relevance to This Study
Bookbinder & Lordahl (1989)	Bootstrap Procedure (Direct Resampling)	The Bootstrap method is preferable to the Normal assumption when the LTD distribution is non-standard.	Foundational approach; does not specifically address complex intermittent demand.

Table 2 (Continue)

Researcher(s) (Year)	Key Method(s) Used	Key Finding(s)	Gap / Relevance to This Study
Willemain et al. (2004)	Bootstrap	The new bootstrap more accurate than Croston's and Exponential Smoothing for intermittent demand.	A complex method focusing primarily on intermittent demand.
Harimansyah & Imaroh (2020)	Cause-and-Effect Diagram, Multiple Forecasting Methods	Inaccurate forecasting is a primary contributor to high inventory levels.	Did not classify demand types in detail before selecting forecasting methods.
Thummathid (2020)	Croston's Method, Holt's Linear, Neural Network	The Neural Network model yielded the highest forecasting accuracy for intermittent demand.	Did not directly compare with the Bootstrap Method.
Baisariyev et al. (2021)	Bootstrap Method	The Bootstrap Method offered higher accuracy in managing intermittent demand.	Noted that the Bootstrap Method had limitations when applied to lumpy demand.
Fan et al. (2023)	Intermittent Feature Adaptation (Clustering before forecasting)	Grouping data by intermittent features before forecasting improves accuracy.	Supports the classification-first approach; uses a different classification technique (clustering).
Shafi et al. (2023)	Neural Network Model (LSTM) for lumpy and intermittent demand	Neural Network models are effective for irregular demand in aviation and impact safety.	Aviation-specific; represents an advanced AI/Deep Learning approach.
This Study	Demand Classification (ADI, CV^2), Bootstrap, Croston's, Exp. Smoothing	N/A	Systematically classifies demand into 4 patterns and applies an appropriate method to each for comparison in a real-world case study.

3. RESEARCH METHODOLOGY

The population for this study comprises all spare part items used in unscheduled maintenance within the case study organization. The 58 parts analyzed were selected based on an ABC Analysis, representing the highest-value items (Group A); this can be considered a form of purposive sampling. Historical usage data spanning five years (2018-2022) were collected from the Enterprise Resource Planning (ERP) system of the case study organization. The data preprocessing procedure then involved verifying the integrity of this historical data and removing any clear data entry errors. Initial data management was performed using Microsoft Excel, while all data analysis, classification, and the development of forecasting models were conducted using the Python programming language. To compare the forecasting performance between the proposed and current methods, this study selected the Mean Squared Error (MSE) as the primary performance metric, as it gives more weight to larger errors. The research methodology is divided into four key stages:

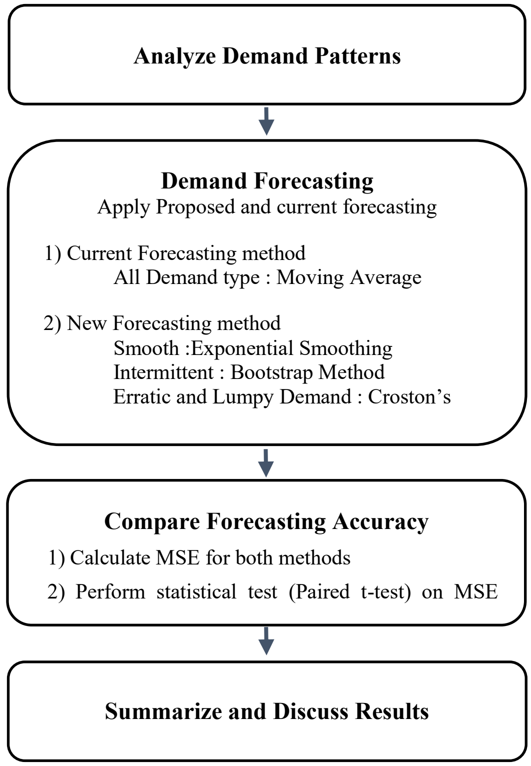

Figure 1 Research Process Diagram

3.1 Analyze Demand Patterns

In this stage, the demand pattern of each spare part is analyzed and classified using two key indicators: the Average Demand Interval (ADI) and the Squared Coefficient of Variation (CV^2). Both indicators are computed using the five-year historical demand data. The classification of demand patterns follows the criteria adapted from Thummathid (2020), as outlined below:

- ADI $\leq$ 1.32 and $CV^2 \leq 0.49$ → Smooth Demand
- ADI > 1.32 and $CV^2 \leq 0.49$ → Intermittent Demand
- ADI $\leq$ 1.32 and $CV^2 > 0.49$ → Erratic Demand
- ADI > 1.32 and $CV^2 > 0.49$ → Lumpy Demand

The Average Demand Interval (ADI) measures the average number of periods between successive demand occurrences and is calculated using the formula Thummathid (2020):

$$ADI = \frac{\text{Total number of time periods}}{\text{Number of non}-\text{zero demand occurrences}}$$

To measure variability, the Coefficient of Variation (CV) is calculated as follows:

$$CV = \frac{\sqrt{\frac{\sum_{t=1}^{N}(d_i^n - d_i)^2}{N}}}{d_i}$$

where:

N = Number of periods with non-zero demand

d_i^n = Demand quantity in period i

d_i = Mean demand during non-zero periods

Then, the squared value of CV, CV^2, is used in conjunction with ADI to classify the demand patterns as noted above. This classification is critical for selecting appropriate forecasting techniques in the subsequent steps.

3.2 Demand Forecasting

In this step, two forecasting approaches are applied to the historical demand data of the selected spare parts:

1. The current method used by the case study organization: Moving Average (3-period)
2. The proposed method in this research involves selecting a forecasting technique that is tailored to the classified demand pattern of each spare part. Specifically, Exponential Smoothing is applied to items with Smooth Demand, the Bootstrap Method is used for those with Intermittent Demand, and Croston's Method is employed for items exhibiting either Erratic or Lumpy Demand. This pattern-based forecasting strategy aims to improve accuracy by aligning the forecasting model with the actual behavior of each spare part's demand.

3.3 Compare Forecasting Accuracy

This step involves evaluating and comparing the forecasting accuracy between the current method (Moving Average, 3-period) and the proposed methods based on demand pattern classification. The Mean Squared Error (MSE) is used as the performance metric to assess forecast accuracy. MSE is calculated for both methods, and the resulting values are compared to determining which method produces the lowest forecasting error. Furthermore, a Paired t-test is conducted on the MSE results to statistically determine if the performance difference between the two approaches is significant.

3.4 Summarize and Discuss Results

The final step summarizes the forecasting results and discusses the implications of the findings. The discussion focuses on how the use of pattern-specific forecasting methods affects forecast accuracy and inventory management. Recommendations for improving spare parts forecasting and broader applications of the methodology are also addressed.

4. RESULTS AND DISCUSSION

The findings of this study are presented in two parts. The first part focuses on the analysis of demand patterns for aircraft spare parts, which were classified based on historical usage data using the Average Demand Interval (ADI) and the Squared Coefficient of Variation (CV^2). The second part presents the results of the demand forecasting, where the proposed forecasting techniques were applied according to each identified demand pattern and compared against the current method used by the organization to evaluate forecasting performance and accuracy.

4.1 Demand Pattern Analysis Results

To identify the demand patterns of each spare part, the Average Demand Interval (ADI) and the Squared Coefficient of Variation (CV^2) were calculated using five years of historical usage data. Based on these indicators, each part was categorized into one of four demand patterns: Smooth, Intermittent, Erratic, or Lumpy.
A sample of the classification results is shown in Table 3, which presents the calculated ADI and CV^2 values, along with the corresponding demand pattern for each spare part.

Table 3 Example of Demand Pattern Classification Results

Part ID	ADI	CV²	Demand Pattern
A000A-243	1.250	0.120	Smooth
A000A-161	1.000	0.100	Smooth
A000A-072	5.000	0.000	Intermittent
A000A-582	5.000	0.000	Intermittent
A000A-261	2.500	0.000	Intermittent
A000A-119	1.667	0.125	Intermittent
A000A-093	5.000	0.000	Intermittent
A000A-094	5.000	0.000	Intermittent
A000A-221	1.667	0.653	Lumpy
A000A-370	1.000	0.839	Erratic

A summary of the demand pattern classification for all 58 spare part items is presented in Table 4.

Table 4 Summary of Demand Pattern Classification by Spare Part Type

Demand Pattern	Count of Item	Percentage (%)
Intermittent Demand	38	65.52%
Smooth Demand	18	31.04%
Erratic Demand	1	1.72%
Lumpy Demand	1	1.72%

As shown in Table 4, most spare parts (38 items or 65.52%) fall into the Intermittent Demand category, indicating sporadic and unpredictable usage. The second most common pattern is Smooth Demand, accounting for 18 items or 31.04%, which reflects regular and stable usage. Both Erratic and Lumpy Demand are the least common, with only one item each, representing 1.72% of the total dataset. These findings suggest that intermittent demand is the predominant challenge in managing spare parts inventory, requiring specialized forecasting approaches to handle its variability effectively.

4.2 Demand Forecasting Results

Following the identification of demand patterns in the previous section, this part presents the demand forecasting results for the selected spare parts. The study introduces a new forecasting method based on the classification of demand types, applying different forecasting techniques tailored to each pattern. Specifically, the Bootstrap Method is used to forecast demand for 38 spare parts identified as having Intermittent Demand. The Exponential Smoothing method is applied to 18 parts classified as having Smooth

Demand, and the Croston's Method is used for parts with Erratic and Lumpy Demand, with one item in each category.

In addition to the new approach, the current forecasting method used by the organization, which is the Moving Average with a 3-period window, is also applied uniformly to all spare parts. This comparison allows for the evaluation of forecasting performance between a one-size-fits-all technique and a pattern-specific strategy. Table 5 presents sample results for selected spare parts, including actual usage values, forecasts from both methods (current and proposed), and the corresponding Mean Squared Error (MSE) values. This side-by-side comparison provides clear insight into the differences in forecasting accuracy between the two approaches.

Table 5 Sample Forecasting Results Comparing the Proposed and Current Methods

Part ID	Demand Pattern	Proposed Forecasting method	Current Forecasting Method	Actual	Current Forecasting	New Forecasting	Current MSE	Proposed MSE
A000A-243	Smooth	Exponential Smoothing	Moving Average	1.00	0.67	0.00	0.11	1.00
A000A-151	Intermittent	Bootstrap	Moving Average	0.00	0.00	0.20	0.00	0.04
A000A-019	Intermittent	Bootstrap	Moving Average	1.00	0.00	0.20	1.00	0.64
A000A-218	Intermittent	Bootstrap	Moving Average	0.00	0.33	0.20	0.11	0.04
A000A-152	Intermittent	Bootstrap	Moving Average	0.00	0.33	0.20	0.11	0.04
A000A-584	Intermittent	Bootstrap	Moving Average	1.00	0.67	0.39	0.11	0.38
A000A-238	Intermittent	Bootstrap	Moving Average	0.00	0.00	0.39	0.00	0.15
A000A-072	Intermittent	Bootstrap	Moving Average	0.00	0.67	0.39	0.45	0.15
A000A-371	Erratic	Croston's	Moving Average	0.00	5.00	4.88	4.00	3.53
A000A-208	Smooth	Exponential Smoothing	Moving Average	1.00	2.67	2.00	2.79	1.00

The forecasting results were further visualized using a line chart, as shown in Figure 2, which compares the Mean Squared Error (MSE) of the current and proposed forecasting methods across all spare part items. The chart clearly illustrates that the proposed forecasting approach consistently produces lower forecasting errors than the current method. Specifically, the average MSE for the proposed method is 1.51, whereas the current method yields a significantly higher average MSE of 1.85. These results demonstrate that the forecasting techniques selected based on demand patterns offer substantially improved accuracy. In summary, the proposed approach provides more reliable forecasts for spare parts demand, supporting better inventory planning and reducing the likelihood of overstocking or shortages compared to the one-size-fits-all method currently in use.

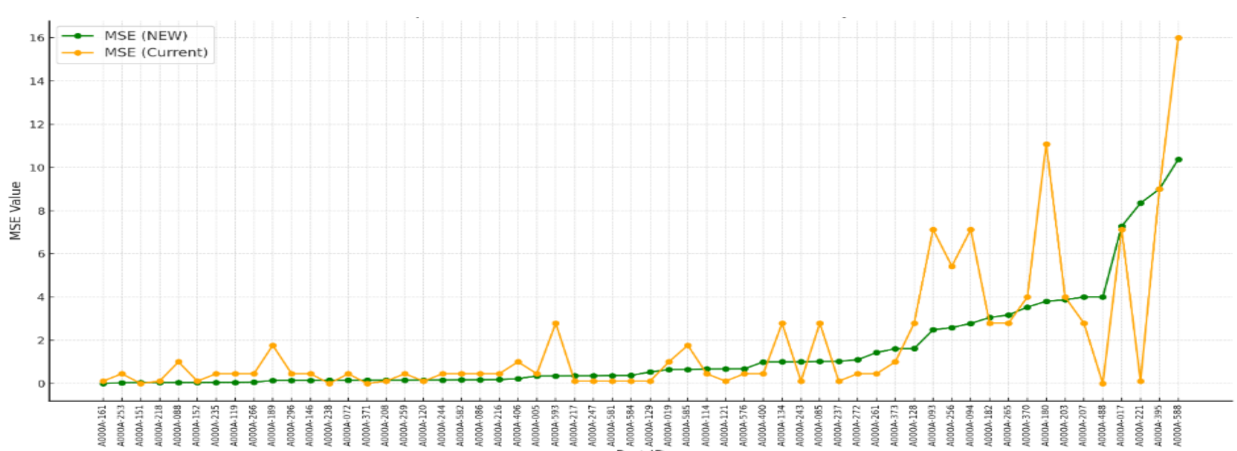

Figure 2 Mean Squared Error (MSE) comparison between the current method (Moving Average)

and the proposed pattern-specific forecasting methods across all 58 spare part items.

To further analyze the performance of the proposed framework, the forecasting errors were aggregated by each of the four demand patterns. Table 6 presents a summary of the average Mean Squared Error (MSE) for both the current and proposed methods within each category.

Table 6 Aggregated Forecasting Errors (MSE) by Demand Pattern

Demand Pattern	Number of Items	Average MSE Current	Average MSE Proposed
Intermittent	38	1.15	0.66
Smooth	18	3.33	2.80
Erratic	1	4.00	3.53
Lumpy	1	0.10	8.35

To formally assess whether the observed improvements in MSE were statistically significant, a series of paired t-tests were conducted. The tests compared the MSE values from the proposed method against the current method for the overall dataset and for the main demand pattern subgroups. The results of these statistical tests are summarized in Table 7.

Table 7 Summary of Paired t-test Results for Forecast Accuracy (MSE)

Data Group	N (pairs)	t-statistic	p-value (one-tail)	Statistically Significant (at $\alpha = 0.05$)
Intermittent	38	1.88	0.034	Significant
Smooth	18	0.64	0.264	Not Significant
Erratic	1	N/A	N/A	N/A
Lumpy	1	N/A	N/A	N/A
Overall	58	1.28	0.103	Not Significant

4.3 Discussion of Findings

This study supports the findings of Harimansyah and Imaroh (2020), who addressed excessive spare parts inventory caused by inaccurate forecasting and suggested using multiple forecasting techniques to improve accuracy. Similarly, Thummathid (2020) highlighted the difficulties in forecasting intermittent demand, which corresponds to the demand pattern found in most of the parts analyzed in this study. Out of 58 spare part items, 38 were classified as intermittent demand, confirming that irregular demand is the dominant challenge in aircraft maintenance inventory. Baisariyev et al. (2021) also demonstrated the effectiveness of the Bootstrap Method for handling unpredictable demand, which is consistent with the improved performance observed in this study when the method was applied to intermittent-demand items.

Compared to these studies, the present research goes further by applying a pattern-specific forecasting framework. The results show that this approach yields a lower average Mean Squared Error (MSE) of 1.51 compared to the 1.85 from the current Moving Average method, reflecting an overall improvement of 18.37%.

Examining the practical impact for each demand type, the Bootstrap Method reduced forecast error for the Intermittent group by approximately 42.61%, while Exponential Smoothing and Croston's Method achieved 15.91% and 11.75% improvements for Smooth and Erratic demand, respectively. Conversely, the Lumpy item exhibited a decline in accuracy, likely due to the inherent volatility and limited sample size. On average, this tailored approach yielded an 18.37% improvement across all demand types when compared to the current Moving Average method.

A series of paired t-tests were conducted to determine if this improvement was statistically significant. For the dominant Intermittent demand group (38 items), the test revealed a statistically significant difference ($p = 0.034$), providing strong evidence that the proposed Bootstrap method is superior for this challenging demand pattern. Conversely, for the 18 smooth demand items, the difference in performance between Exponential Smoothing and the Moving Average was not statistically significant ($p = 0.264$). A statistical comparison for the Erratic and Lumpy patterns was not feasible as each category contained only a single item.

In terms of practical application, these findings are highly valuable for the case study organization. The significant improvement for intermittent-demand parts can directly lead to more optimized inventory levels, reducing holding costs and minimizing the critical risk of stockouts, which could otherwise lead to an Aircraft on Ground (AOG) situation. Furthermore, the proposed pattern-specific framework is not limited to the aviation industry and could be applied to other sectors facing similar irregular demand challenges, such as in the automotive, electronics industries. For future research, it is recommended to explore more advanced machine learning models. Techniques such as Artificial Neural Networks and deep learning approaches like Long Short-Term Memory (LSTM) networks could potentially offer even greater accuracy, especially if more granular data becomes available.

5. CONCLUSION

This research aimed to analyze the patterns and characteristics of aircraft spare parts demand in unscheduled maintenance operations and to propose forecasting methods that align with the specific demand behavior of each item. The study focused on 58 high-usage spare parts, classified as Group A items through ABC Analysis, based on five years of historical usage data (2018–2022). The goal was to recommend forecasting techniques that improve demand prediction accuracy and inventory planning effectiveness.

The analysis revealed that the majority of spare parts exhibit Intermittent Demand, accounting for 38 items or 65.52% of the dataset. Smooth Demand was the second most common pattern, observed in 18 items (31.04%). Erratic and Lumpy Demand were the least common, each found in only one item (1.72%). These findings highlight that irregular demand dominates the spare parts inventory in aircraft maintenance operations, reinforcing the necessity of specialized forecasting methods tailored to such variability.

The comparative evaluation of forecasting methods demonstrated that the traditional Moving Average technique resulted in an average Mean Squared Error (MSE) of 1.85, whereas the proposed pattern-specific forecasting approach achieved a significantly lower average MSE of 1.51. This represents an 18.37% reduction in forecasting error. Therefore, the study clearly concludes that matching forecasting techniques to actual demand patterns leads to more accurate predictions and more effective inventory management for aircraft spare parts.

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