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# Forecasting Consumable Part for Aircraft Maintenance using Time Series Method

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***Abstract:***
This study discusses the inventory of consumable parts at an aircraft maintenance company in Bandung. The problem that occurs is that companies often face stock shortages. Another issue is that the warehouse has excess stock of materials that have an expiration date, which is financially detrimental to the company. To overcome this, the study categorizes materials using the ABC and ADI CV2 analysis methods. After obtaining the demand patterns including smooth demand, intermittent demand, erratic demand, and lumpy demand forecasting is carried out according to the demand pattern using Exponential Smoothing, Croston, Syntetos Boylan Approximation, and Teunter Syntetos Babai. The data used is PT XYZ consumable part data from January 2022 to December 2023. After analysis and testing the level of forecast accuracy using MAD, MSE, and MAPE, the results showed that the Croston, SBA, and TSB forecasting methods each offer their own advantages based on the specific characteristics of the demand pattern applied.

**Keywords:** Inventory; Consumable Parts; Aircraft Maintenance Company

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## INTRODUCTION

The aviation industry is one of the most competitive business sectors and critical component of the global economy (Halteh, AlKhoury, Adel Ziadat, Gepp, & Kumar, 2024). Especially the aircraft maintenance industry. Every aircraft maintenance company is required to always innovate in order to have high competitiveness. Parts are the most important part of an aircraft industry. This components, which is one of the four main maintenance activities, annually absorbs more than 20% of airline maintenance expenditure (CAO, ZHANG, & FENG, 2024). So the availability of spare parts is a key factor in the aircraft maintenance industry (Nafiurridha & Choiruddin, 2024). Each spare part has an important role in maintaining performance and safety in flight. By International Air Transport Association, aircraft parts are classified into 3 types: routable part, repairable part and consumable part. In a maintenance, damaged or worn parts must be replaced immediately with new ones (İfraz, Aktepe, Ersöz, & Çetinyokuş, 2023).

Inventory is an important component in the supply chain (Xiao, Ma, Wang, & Huang, 2024). Maintaining a spare parts inventory is essential in serving aircraft maintenance (Antosz & Ratnayake, 2019). Forecasting parts demand in the supply chain is essential to ensure customer satisfaction while minimizing inventory accordingly (Chien, Ku, & Lu, 2023). Due to the different nature of the parts, the demand is often high for some items and low for others, resulting in overstocking (Sareminia & Amini, 2023). The main challenge faced by airlines is that decisions on how to predict these items are very challenging, as they are characterized by sporadic, highly intermittent and varied demand (Flávio, Almeida, Cássia, & Lima, 2024).

3 types of aircraft parts, consumable part is a spare part that has consumable properties and has an expiration date. Different from other spare parts that can be repaired. This research was conducted in PT XYZ aircraft maintenance division, where consumable parts run often shortage and some types of goods that have an expiration date are overstock. If the item has expired, it cannot be used and loss. Having a large amount of inventory will also incur large storage costs. Consumable parts are very important to support the work in this aircraft maintenance company. If the consumable parts are not met, the work will be downtime, not only causing delays in the completion of the work but due to this delay the company will be subject to penalties according to the contract agreement. To solving this problem, accurate forecasting is needed, so that we can predict future demand more precisely, and also carrying out good inventory control will minimize the risk of company losses due to shortage and overstock. Firstly, to perform forecasting consumable part in the aircraft maintenance industry, material classification is carried out first using ABC analysis. This is a commonly used classification in inventory management, where items are grouped into 3 classes based on the importance of each item (İfraz dkk., 2023). In previous research, classification with this method has also been carried out in the aviation industry (Pradini & Kusumastuti, 2023) and automotive industry (M. H. Kibria, 2020). Then reclassification is carried out according to the demand pattern using the ADI-CV2 method which has categories namely smooth, intermittent, erratic and lumpy (Şahin, Eldemir, & Turkyilmaz, 2022b).

In conducting spare parts forecasting, this study will use the exponential smoothing for stable demand or smooth. This ES will be accurate if it has stable demand data and does not fluctuate too much. If it has a trend, the method is not reliable for making decisions (Pinçe, Turrini, & Meissner, 2021). For demand data with high fluctuations or periods without demand, it will use the Croston which has been widely used as a method of intermittent forecasting before (Ramadhan & Santosa, 2021). Then also using the Syntetos and Boylan Approximation (SBA) for comparators, as an enhanced method of the Croston. This SBA method allows obtaining unbiased forecasting (M. H. Kibria, 2020). In this research (Kaya, Sahin, & Demirel, 2020) on aircraft maintenance, the forecasting result explain croston is good for smooth and erratic demand, While SBA is good for intermittent and lumpy demand. The last method of comparison is to use the Teunter-Syntetos-Babai (TSB). If the Croston and SBA show good results when there is an intermittent pattern, but both have limitations in overcoming situations where the requested product has obsolescence (Yang, Ding, Lee, Yu, & Ma, 2021). Obsolescence occurs when the demand for a product drops drastically or stops altogether because it has a better replacement product. Method Croston and the SBA will tend to give high forecasts because it does not account for a decline in demand (Babai, Dallery, Boubaker, & Kalai, 2019b).

ABC Analysis is a method that is often used in classifying spare parts and inventory based on value or contribution total value, because its application is simple and easy to understand (Cakmak & Guney, 2023). This analysis explains that 20% contributes most of the total inventory value around 80% and conversely, most items 80% contribute only a small part of the total value (Pradini & Kusumastuti, 2023). ABC analysis divides inventory items into several classes based on value (Reid & Sanders, 2011). Class A is high-value items that require special care. Class B is ordinary-value items that require standard care and class C is low-value items that require little care.

ADI-$CV^2$ Analysis has 4 types of categories: smooth, intermittent, erratic, and lumpy (Şahin, Eldemir, & Turkyilmaz, 2022a). Intermittent data has most of the demand for zero, while non-zero demand has random values with small variations. For erratic demand, it has sporadic demand, the amount varies very high and the interval between two existing requests can be very long. Finally, the smooth demand pattern has regular demand, the amount is relatively stable, and there is rarely a period without demand (Kaya dkk., 2020). the categorization scheme uses 2 demand parameters, average demand interval (ADI) and coefficient of variation square (CV2) (Ramadhan & Santosa, 2021).

Forecasting is an activity of predicting what will happen in the future by using historical data that is explained mathematically or by relying on intuition from experience (Makridakis, Spiliotis, & Assimakopoulos, 2022). Single exponential smoothing one of the popular forecasting methods used to predict future values based on historical data (Kumar, Sharma, & Khedlekar, 2024). This method is useful when the data is stable or has little trend (da Silva dkk., 2024). In previous research, forecasting on nose tire Boeing 737-300 using single exponential smoothing shows more accurate results compared to the naïve and moving average method (Sondeng, Mandagie, & Tedja, 2021). whereas holt exponential smoothing this forecast is used when the data shows a trend or tendency to increase or decrease consistently over time (Shejul, Harikrishnan, & Gupta, 2024). In previous research, forecasting of the number of goods loaded at the airport was carried out using holt exponential smoothing and ANN (Artificial Neural Network). The result is holt exponential smoothing is better method than ANN with smallest error value (Marpaung, Rusgiyono, & Wilandari, 2023). In the research on airplane passengers, forecasting was also carried out. The results showed that forecasting with the holt method on smooth data had good results with the smallest error (Ramadiani, Syahrani, Astuti, & Azainil, 2020).

For intermittent demand, the method used is the Croston method. which method is used with periods without demand. Croston does not only predict the volume of demand, but also the time interval between two requests (Şahin dkk., 2022a). In previous research, Forecasting has been carried out on aircraft components by comparing Croston and SBA method. The result is Croston gave the lowest erroneous results for most part estimates. It has been seen that the Croston method can be easily used in estimating the demand for non-uniform and intermittent spare parts (Ekin, 2022). while in other studies SBA is an improved method of the Croston method. Based on (Svetunkov & Boylan, 2023) SBA forecasting shows high accuracy value compared to Croston. This forecast is more accurate when the demand interval is greater than 1.25 time periods (Mz, Tsakalerou, & Ct, 2021). In previous research, A company can carry out preventive activities so that death stock inventory doesn't arise due to new procurement activities by calculating intermittent demand patterns using the SBA method (Ridwan Harimansyah & Tukhas Shilul Imaroh, 2020). in some academic literature Croston and SBA provides excellent inventory estimates and performance. However, they update demand sizes and demand interval only in periods with positive demand, so in periods with zero demand the forecast is not adjusted. TSB provides a solution by updating its probabilities and doing so every period (Doszyń & Dudek, 2024). Teunter Syntetos Babai has a more flexible and accurate method especially in handling changing demand patterns (Doszyn, 2021). This model is more responsive to changes in demand patterns. The TSB method is still rarely used, especially in the aviation industry. In previous research in industry military and automotive, doing forecast by comparing the Croston, SBA and TSB method. The result shows TSB method has good performance in overcoming obsolescence (Babai, Dallery, Boubaker, & Kalai, 2019a).

Previous studies have explored demand forecasting and inventory optimization in various industries, yet limited research has been specifically directed toward consumable parts in aircraft maintenance with expiration characteristics. Ramadhan and Santosa (2021) highlighted the effectiveness of Croston and SBA methods for intermittent demand forecasting, particularly in manufacturing and logistics industries. Meanwhile, Şahin, Eldemir, and Turkyilmaz (2022) investigated the classification of demand patterns in aviation spare parts, emphasizing the role of ADI-CV² methods for categorizing erratic and lumpy demands. However, these studies did not address the complexity posed by consumable spare parts that expire, nor did they combine ABC and ADI-CV² classification with various intermittent forecasting methods under the specific constraints of aircraft maintenance operations. This study fills the gap by evaluating and comparing exponential smoothing (ES), Croston, SBA, and Teunter-Syntetos-Babai (TSB) methods to determine the most accurate forecasting technique for consumable aircraft parts at PT XYZ. This study aims to find which forecasting has the best accuracy to be implemented in companies engaged in aircraft maintenance. Doing good forecasting and good inventory control will minimize the risk of running out and overstocking. The results are expected to provide strategic insights for maintenance planners in aviation, contributing to better supply chain responsiveness, reduced operational risks, and improved resource utilization, especially for critical and time-sensitive consumable components.

## RESEARCH METHOD

This research was conducted in PT XYZ. Historical data was collected on monthly material demand and prices, starting from January 2022 to December 2023. After all the data was collected, a material categorization analysis was carried out based on the annual value of each item, classifying materials based on their demand patterns, making forecasts and testing the accuracy of the forecast results. This method can be implemented in other industry where inventory systems also deal with sporadic demand and long lead times. The methodological approach and insights regarding demand classification and model selection offer valuable guidance for broader applications in supply chain and inventory management across sectors facing similar forecasting challenges.

ABC Analysis is to classify materials based on value or contribution to the total value of the inventory. This category is divided into 3 categories, namely, categories A, B and C. Categories A is high value product with low sales frequency, categories B is a moderate value product with low sales frequency, and categories C is a low value product with high sales frequency. The following are the procedures that must be done in conducting an ABC Analysis (Reid & Sanders, 2011). First, calculate the annual value for each item. After that list items in descending order based on their annual consumption. And then calculate the cumulative percentage of the item and its annual consumption value. Hence, we can focus on high value items, avoid overstock and minimize waste.

ADI-$CV^2$ is a classification based on demand patterns using ADI-$CV^2$ analysis. This category has 4 types of categories; smooth, intermittent, erratic, and lumpy. In this analysis 2 parameters are used, Average Demand Interval (ADI) measures how frequently a product experience demands over a given time. They can be expressed as:

$$\mathrm{ADI} = \frac{\sum_{i=1}^{N} t_i}{N} \tag{1}$$

and Coefficient of Variation Square ($CV^2$) measures variability of demand. It can be expressed as:

$$\mathrm{CV2} = \frac{\sqrt{\frac{\sum_{i=1}^{n}(\varepsilon_i - \varepsilon)^2}{N}}}{\varepsilon} \tag{2}$$

ε It can be obtained by the following equation

$$\varepsilon = \frac{\sum_{i=1}^{N} \varepsilon_i}{N} \tag{3}$$

where N is the total number of periods, $\varepsilon_i$ is the demand for period, and ε is the average demand for all periods. If the material demand pattern is smooth, then ADI < 1.32 and $CV^2$ < 0.49. If intermittent, then ADI >= 1.32 and $CV^2$ < 0.49. If erratic then, ADI < 1.32 and $CV^2$ >= 0.49. If lumpy, then ADI >= 1.32 and $CV^2$ >= 0.49.

Forecasting is carried out, if the material demand pattern is smooth, the exponential smoothing forecasting method will be used. It consists of single exponential smoothing where this method has more stable data and has fewer trends. With the following equation:

$$\mathrm{Ft} + 1 = \alpha \mathrm{Xt} + (1 - \alpha)\,\mathrm{Ft} - 1$$
(4)

where Ft + 1 is forecast for the next period, α is parameter value between 0 – 1, $X_t$ is actual value for time, and Ft – 1 is forecast for the previous period. Holt exponential smoothing, where this method has data that shows the existence of a trend or tendency to rise or fall consistently over time. This method has 2 equations, namely the equation for predicting the level. With the following equation:

$$\mathrm{St} = \alpha \mathrm{Yt} + (1 - \alpha)(\mathrm{St} - 1 + \mathrm{bt} - 1) \tag{5}$$

where $S_t$ is exponential smoothing value, α is smoothing constant ( $0 < \alpha < 1$ ), Yt is actual demand period, and $b_t$ is estimated trend. For predicting levels. It can be expressed as:

$$\mathrm{bt} = (\gamma \mathrm{St} - \mathrm{St} - 1) + (1 - \gamma)\,\mathrm{bt} - 1 \tag{6}$$

$b_t$ is trend estimate, $\gamma$ is smoothing constant for trend estimation ($0 < \gamma < 1$), and $S_t$ is exponential smoothing value. The two forecasts are then combined to produce a final forecast for the next period. Here is the equation:

$$\mathrm{Ft} + \mathrm{m} = \mathrm{St} + \mathrm{bt} + \mathrm{m} \tag{7}$$

To find the smoothing constat value, in this research using Microsoft Excel to optimized smoothing factor by minimizing forecasting errors such as MAD, MAE, and MAPE. The process begins by entering the formula, after that excel solver will find optimal α/γ value. After solver complete the optimization, the best value will product the forecast with lowest error rate.

For forecasting with intermittent demand patterns, comparisons will be made with forecasting methods Croston, Syntetos Boylan approximation (SBA) dan Teunter Syntetos Babai (TSB). Croston specifically designed to handle intermittent demand, which is demand that is often irregular with periods of no demand. This method does not only predict the amount of goods requested, but also takes into account how often the demand occurs. In other words, Croston does not only predict the volume of demand, but also the time interval between two requests. Here is the formula:

$$\mathrm{Yt} = \left\{ \alpha \,.\, x_{t-1} + (1 - \alpha). \begin{matrix} Y_{t-1}, X_{t-1} = 0 \\ Y_{t-1}, X_{t-1} > 0 \end{matrix} \right.$$

$$\mathrm{qt} = \begin{cases} q_{t-1} + 1, & X_{t-1} = 0 \\ 1, & X_{t-1} > 0 \end{cases}$$

$$\mathrm{pt} = \left\{ \alpha \,.\, q_{t-1} + (1 - \alpha). \begin{matrix} p_{t-1}, X_{t-1} = 0 \\ p_{t-1}, X_{t-1} > 0 \end{matrix} \right.$$

$$\mathrm{Ft} = \frac{Y_t}{p_t} \tag{8}$$

Where $X_t$ is the actual demand for period t, $Y_t$ is the average non-zero value, Ft is the forecast demand per period t, $q_t$ is the number of periods after the last period that have demand (non-zero demand period), α is the smoothing constant, $0 \leq \alpha \leq 1$, and $p_t$ is the estimation period interval. Then use forecasting syntetos boylan approximation (SBA). With the following equation:

$$\mathrm{Ft\,(SBA)} = \left(1 - \frac{\alpha}{2}\right) \frac{Y_t}{p_t} \tag{9}$$

Where Ft is the demand estimate per period t, α is the smoothing constant, $0 \leq \alpha \leq 1$, $Y_t$ is the non-zero mean value, and $p_t$ is the estimation period interval. For the forecasting methods teunter syntetos babai (TSB). With the following equation:

$$\mathrm{pt\,(TSB)} = \begin{cases} (1 - \beta).\, p_{t-1} & p_{t-1}, X_{t-1} = 0 \\ \beta + (1 - \beta).\, p_{t-1} & p_{t-1}, X_{t-1} > 0 \end{cases}$$

$$\mathrm{Ft\ (TSB)} \quad = \mathrm{Yt\,.\,pt}$$
(10)

Where Ft is forecast demand per period t, β is smoothing constant, 0 ≤α ≤ 1, $Y_t$ = Non-zero mean value, and $p_t$ = Estimation period interval.

Based on the book Operation Management (Reid & Sanders, 2011) there are 3 most popular measures for carrying out forecast accuracy to ensure that the forecast is performing well.

Mean Absolute Deviation (MAD). With the following equation:

$$\text{MAD} = \frac{\sum |\text{Actual} - \text{Forecast}|}{n} \quad (11)$$

Mean Absolute Error (MAE). With the following equation:

$$\text{MAE} = \frac{\sum |\text{FORECAST ERROR}|^2}{n} \quad (12)$$

Mean Absolute Percentage Error (MAPE). With the following equation:

$$\text{MAPE} = \frac{\sum_{i=1}^{n} 100|\text{Actual} - \text{Forecast}|\frac{1}{\text{Actual}}}{n} \quad (13)$$

## RESULT AND DISCUSSION

In this research, classification is carried out based on the value of contribution to the total value of inventory with ABC analysis. Furthermore, classification based on demand patterns is carried out with ADI-CV2 analysis, so that forecasting can be carried out using exponential smoothing, croston, boylan syntetos approximation and teunter syntetos babai to find the best forecasting. After that, the accuracy level was tested using MAD, MSE and MAPE.

### Material Categorization

In this analysis, the categorization of goods is carried out based on their value or contribution to the total value of inventory. This category will be divided into 3 namely, categories A, B and C. It aims to manage inventory more efficiently and know which materials should be prioritized. Each category takes the top 5-part numbers to be analyzed by ADI-CV2. The following is the classification that has been carried out based on the ABC analysis:

**Tabel 1. ABC Analysis Result**

| No. | **Part Number** | **demand** | **price (USD)** | **Total price (USD)** | **Material price** | **Cumulative price** | **Category** |
|---|---|---|---|---|---|---|---|
| 1 | EASTMAN-TO2380 | 209 | 240,00 | 50160,00 | 16,17 | 16,17 | A |
| 2 | S15/90 | 65 | 641,00 | 41665,00 | 13,43 | 29,61 | A |
| 3 | RENLAM-LY560 + REN-HY560-TS | 20 | 1035,88 | 20717,60 | 6,68 | 36,29 | A |
| 4 | ARDROX9PR5 | 177 | 108 | 19116,00 | 6,16 | 42,45 | A |
| 5 | PR1782B2 | 91 | 172,00 | 15652,00 | 5,05 | 47,50 | A |
| 6 | FREKOTE700NC | 31 | 185,00 | 5735,00 | 1,85 | 72,81 | B |

| No. | Part Number | demand | price (USD) | Total price (USD) | Material price | Cumulative price | Category |
|---|---|---|---|---|---|---|---|
| 7 | LPS3 (00305) | 14 | 405,77 | 5680,78 | 1,83 | 74,64 | B |
| 8 | CA1010 | 52 | 102,80 | 5345,60 | 1,72 | 76,36 | B |
| 9 | AEROSHEL-FLUID41 | 42 | 125,00 | 5250,00 | 1,69 | 78,05 | B |
| 10 | AW106 | 49 | 87 | 4263,00 | 1,37 | 79,43 | B |
| 11 | C25/90S | 14 | 109,50 | 1533,00 | 0,49 | 91,33 | C |
| 12 | BB3100 | 5 | 287,33 | 1436,65 | 0,46 | 91,80 | C |
| 13 | PAINT BRUSH21/2INCH | 85 | 16,00 | 1360,00 | 0,44 | 92,24 | C |
| 14 | Aeroshell Turbine Oil 2 | 21 | 63,96 | 1343,16 | 0,43 | 92,67 | C |
| 15 | PAINTBRUSH2INCH | 74 | 18,00 | 1332,00 | 0,43 | 93,10 | C |

In this analysis, ABC classified consumable parts into 3 categories, namely, A, B and C. After that, each category of the top 5-part numbers from each category was selected to be focused on in the next analysis. For category A which has the highest score of 70% of the total. For category B which has a value of 20% of the total and for category C which has a value of 10% of the total.

In this analysis, a classification method based on demand patterns is carried out. This average demand interval measures the average time interval between two requests, while Coefficient of Variation measures the spread of time intervals. In theory, this category has 4 demand patterns, namely smooth, intermittent, erratic and lumpy. The following are the results of the ADI-CV2 analysis:

**Tabel 2. ADI-CV Analysis Result**

| No. | Part Number | Price (USD) | Category | ADI | Stdv | Mean | CV2 | Demand Pattern |
|---|---|---|---|---|---|---|---|---|
| 1 | EASTMAN-TO2380 | 240,00 | A | 1,00 | 5,40 | 8,71 | 0,38 | Smooth |
| 2 | S15/90 | 641,00 | A | 2,00 | 3,39 | 2,71 | 1,57 | Lumpy |
| 3 | RENLAM-LY560 + REN-HY560-TS | 1035,88 | A | 3,00 | 1,52 | 0,83 | 3,34 | Lumpy |
| 4 | ARDROX9PR5 | 108 | A | 1,41 | 7,29 | 7,38 | 0,98 | Lumpy |
| 5 | PR1782B2 | 172,00 | A | 1,09 | 2,60 | 3,79 | 0,47 | Smooth |
| 6 | FREKOTE700NC | 185,00 | B | 2,18 | 1,60 | 1,29 | 1,54 | Lumpy |
| 7 | LPS3 (00305) | 405,77 | B | 3,42 | 0,93 | 0,58 | 2,53 | Lumpy |
| 8 | CA1010 | 102,80 | B | 1,00 | 1,27 | 2,17 | 0,35 | Smooth |
| 9 | AEROSHEL-FLUID41 | 125,00 | B | 1,71 | 1,78 | 1,75 | 1,03 | Lumpy |
| 10 | AW106 | 87 | B | 1,71 | 2,42 | 2,04 | 1,41 | Lumpy |
| 11 | C25/90S | 109,50 | C | 4,00 | 1,06 | 0,58 | 3,30 | Lumpy |
| 12 | BB3100 | 287,33 | C | 4,80 | 0,41 | 0,21 | 3,97 | Lumpy |
| 13 | PAINT BRUSH21/2INCH | 16,00 | C | 1,00 | 2,59 | 3,54 | 0,53 | Erratic |

| No. | Part Number | Price (USD) | Category | ADI | Stdv | Mean | CV2 | Demand Pattern |
|---|---|---|---|---|---|---|---|---|
| 14 | Aeroshell Turbine Oil 2 | 63,96 | C | 3,42 | 1,42 | 0,88 | 2,65 | Lumpy |
| 15 | PAINT BRUSH2INCH | 18,00 | C | 1,00 | 2,04 | 3,08 | 0,44 | Smooth |

Based on the results of the ADI-CV analysis, there are 4-part numbers that have a smooth demand pattern. Furthermore, there is 1 part number that has an erratic demand pattern. Finally, there are 10 part numbers that have a lumpy demand pattern. After the ADI-CV analysis in this study, no demand with an intermittent demand pattern was found.

**Forecasting**

In this analysis, forecasting is carried out based on demand patterns. For smooth demand will use exponential smoothing forecasting which consists of single exponential smoothing and holt exponential smoothing. For erratic demand patterns and Lumpy Demand, we will use forecasting methods using Croston, Boylan approximation (SBA) Syntetos and pig Syntetos (TSB).

The following are the results of the forecasting calculation for one of the EASTMAN -TO2380 part numbers using the single exponential smoothing and holt exponential smoothing methods:

**Tabel 3. Calculation P/N EASTMAN -TO2380 With SES**

| Period | Demand | Forecast |
|---|---|---|
| 1 | 10 | - |
| 2 | 20 | 10 |
| 3 | 2 | 12 |
| 4 | 10 | 10 |
| 5 | 20 | 10 |
| 6 | 5 | 12 |
| 7 | 15 | 11 |
| 8 | 10 | 11 |
| 9 | 21 | 11 |
| 10 | 5 | 13 |
| 11 | 8 | 12 |
| 12 | 5 | 11 |
| 13 | 10 | 10 |
| 14 | 4 | 10 |

| Period | Demand | Forecast |
|---|---|---|
| 15 | 5 | 9 |
| 16 | 5 | 8 |
| 17 | 10 | 7 |
| 18 | 4 | 8 |
| 19 | 5 | 7 |
| 20 | 10 | 7 |
| 21 | 5 | 7 |
| 22 | 5 | 7 |
| 23 | 10 | 7 |
| 24 | 5 | 7 |

**Tabel 4. Calculation P/N EASTMAN -TO2380 With HES**

| Periode | Demand | Level | Tren | Forecast |
|---|---|---|---|---|
| 1 | 10 | - | - | - |
| 2 | 20 | 20,00 | 10,00 | - |
| 3 | 2 | 18,36 | 2,08 | 30 |
| 4 | 10 | 16,10 | -0,87 | 20 |
| 5 | 20 | 17,21 | 0,48 | 15 |
| 6 | 5 | 12,42 | -3,11 | 18 |
| 7 | 15 | 11,67 | -1,50 | 9 |
| 8 | 10 | 10,10 | -1,55 | 10 |
| 9 | 21 | 13,72 | 1,97 | 9 |
| 10 | 5 | 11,25 | -1,05 | 16 |
| 11 | 8 | 9,28 | -1,67 | 10 |
| 12 | 5 | 6,52 | -2,41 | 8 |
| 13 | 10 | 6,56 | -0,75 | 4 |
| 14 | 4 | 5,06 | -1,26 | 6 |
| 15 | 5 | 4,30 | -0,92 | 4 |
| 16 | 5 | 4,05 | -0,46 | 3 |
| 17 | 10 | 6,25 | 1,35 | 4 |
| 18 | 4 | 6,11 | 0,33 | 8 |

| Periode | Demand | Level | Tren | Forecast |
|---|---|---|---|---|
| 19 | 5 | 5,84 | -0,08 | 6 |
| 20 | 10 | 7,53 | 1,12 | 6 |
| 21 | 5 | 7,13 | 0,09 | 9 |
| 22 | 5 | 6,30 | -0,54 | 7 |
| 23 | 10 | 7,52 | 0,66 | 6 |
| 24 | 5 | 6,86 | -0,24 | 8 |

The following is a forecast calculation on one of the part numbers S15/90 using the Croston and SBA methods:

**Tabel 5. Calculation S15/90 With Croston and SBA**

| Periode | Demand | Yt | qt | Pt | Croston | SBA |
|---|---|---|---|---|---|---|
| 1 | 2 | 0,40 | 1 | 0,20 | 2,00 | 1,80 |
| 2 | 10 | 2,32 | 1 | 0,36 | 6,44 | 5,80 |
| 3 | 4 | 2,66 | 1 | 0,49 | 5,44 | 4,90 |
| 4 | 4 | 2,92 | 1 | 0,59 | 4,95 | 4,46 |
| 5 | 0 | 2,92 | 2 | 0,87 | 3,35 | 3,02 |
| 6 | 10 | 4,34 | 1 | 0,90 | 4,83 | 4,35 |
| 7 | 0 | 4,34 | 2 | 1,12 | 3,88 | 3,49 |
| 8 | 2 | 3,87 | 1 | 1,09 | 3,54 | 3,18 |
| 9 | 0 | 3,87 | 2 | 1,28 | 3,04 | 2,73 |
| 10 | 0 | 3,87 | 3 | 1,62 | 2,39 | 2,15 |
| 11 | 0 | 3,87 | 4 | 2,10 | 1,85 | 1,66 |
| 12 | 5 | 4,10 | 1 | 1,88 | 2,18 | 1,96 |
| 13 | 0 | 4,10 | 2 | 1,90 | 2,15 | 1,94 |
| 14 | 6 | 4,48 | 1 | 1,72 | 2,60 | 2,34 |
| 15 | 0 | 4,48 | 2 | 1,78 | 2,52 | 2,27 |
| 16 | 6 | 4,78 | 1 | 1,62 | 2,95 | 2,65 |
| 17 | 8 | 5,43 | 1 | 1,50 | 3,62 | 3,26 |
| 18 | 0 | 5,43 | 2 | 1,60 | 3,40 | 3,06 |
| 19 | 6 | 5,54 | 1 | 1,48 | 3,75 | 3,37 |
| 20 | 0 | 5,54 | 2 | 1,58 | 3,50 | 3,15 |
| 21 | 2 | 4,83 | 1 | 1,47 | 3,30 | 2,97 |

| Periode | Demand | Yt | qt | Pt | Croston | SBA |
|---|---|---|---|---|---|---|
| 22 | 0 | 4,83 | 2 | 1,57 | 3,07 | 2,77 |
| 23 | 0 | 4,83 | 3 | 1,86 | 2,60 | 2,34 |
| 24 | 0 | 4,83 | 4 | 2,29 | 2,11 | 1,90 |

**Tabel 6. Calculation P/N S15/90 With TSB**

| Periode | Demand | Probabilitas | Permintaan Rata² | TSB |
|---|---|---|---|---|
| 1 | 2 | 0,20 | 2,00 | 0,40 |
| 2 | 10 | 0,36 | 6,00 | 2,16 |
| 3 | 4 | 0,49 | 5,33 | 2,60 |
| 4 | 4 | 0,59 | 5,00 | 2,95 |
| 5 | 0 | 0,47 | 5,00 | 2,36 |
| 6 | 10 | 0,58 | 6,00 | 3,47 |
| 7 | 0 | 0,46 | 6,00 | 2,77 |
| 8 | 2 | 0,57 | 5,33 | 3,04 |
| 9 | 0 | 0,46 | 5,33 | 2,43 |
| 10 | 0 | 0,36 | 5,33 | 1,94 |
| 11 | 0 | 0,29 | 5,33 | 1,56 |
| 12 | 5 | 0,43 | 6,17 | 2,67 |
| 13 | 0 | 0,35 | 6,17 | 2,14 |
| 14 | 6 | 0,48 | 5,37 | 2,56 |
| 15 | 0 | 0,38 | 5,37 | 2,05 |
| 16 | 6 | 0,51 | 5,44 | 2,75 |
| 17 | 8 | 0,60 | 5,70 | 3,45 |
| 18 | 0 | 0,48 | 5,70 | 2,76 |
| 19 | 6 | 0,59 | 5,72 | 3,36 |
| 20 | 0 | 0,47 | 5,72 | 2,69 |
| 21 | 2 | 0,58 | 5,41 | 3,11 |
| 22 | 0 | 0,46 | 5,41 | 2,49 |
| 23 | 0 | 0,37 | 5,41 | 1,99 |
| 24 | 0 | 0,29 | 5,41 | 1,59 |

### Accuracy Test

The following are the results of the accuracy test of the forecasting calculations of each forecasting method:

**Tabel 7. Result Forecasting Accuracy in Exponential Smoothing**

| No. | Part Number | SES | | | HES | | |
|---|---|---|---|---|---|---|---|
| | | MAD | MSE | MAPE | MAD | MSE | MAPE |
| 1 | EASTMAN-TO2380 | 4,54 | 30,2 | 77,80% | 5,87 | 70,6 | 73,9% |
| 2 | PR1782B2 | 2,1 | 8,36 | 36,8% | 2,63 | 12,1 | 55,3% |
| 3 | CA1010 | 0,9 | 1,56 | 56,39% | 1,5 | 4,8 | 58,16% |
| 4 | PAINT BRUSH 2IN | 2,02 | 7,78 | 76,08% | 2,45 | 11,86 | 96,6% |

**Tabel 8. Result Forecasting Accuracy in Croston, SBA, and TSB**

| No | Part Number | Croston | | | SBA | | | TSB | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | MAD | MSE | MAPE | MAD | MSE | MAPE | MAD | MSE | MAPE |
| 1 | S15/90 | 2,65 | 8,31 | 22,7% | 2,55 | 8,21 | 22,09% | 2,64 | 9,55 | 27,1% |
| 2 | RENLAM-LY560 + REN-HY560-TS | 1,01 | 1,93 | 17,2% | 0,99 | 1,96 | 18,8% | 0,93 | 1,92 | 17,9% |
| 3 | ARDROX9PR5 | 4,757 | 40,1 | 16,6% | 4,752 | 40,2 | 18,3% | 5,14 | 46,5 | 24,6% |
| 4 | FREKOTE700NC | 1,27 | 2,18 | 19,61% | 1,27 | 2,2 | 22,2% | 1,24 | 2,12 | 24,8% |
| 5 | LPS3 (00305) | 0,72 | 0,75 | 20,4% | 0,71 | 0,76 | 21.3% | 0,67 | 0,65 | 19,03% |
| 6 | AEROSHEL-FLUID41 | 1,25 | 2,28 | 17,4% | 1,26 | 2,31 | 19,6% | 1,34 | 2,63 | 22,02% |
| 7 | AW106 | 1,89 | 4,57 | 19,99% | 1,87 | 4,6 | 21,3% | 1,94 | 4,96 | 27,5% |
| 8 | C25/90S | 0,77 | 0,9 | 15,2% | 0,75 | 0,91 | 16,2% | 0,74 | 0,88 | 17,5% |
| 9 | BB3100 | 0,28 | 0,15 | 16,3% | 0,27 | 0,15 | 16,8% | 0,26 | 0,13 | 15,05% |
| 10 | PAINT BRUSH21/2INCH | 1,54 | 3,89 | 76,9% | 1,48 | 3,71 | 67,09% | 1,82 | 7,26 | 70,62% |
| 11 | AeroshellTurbine Oil 2 | 1,09 | 1,69 | 18,65% | 1,07 | 1,72 | 19,7% | 1,02 | 1,57 | 18,06% |

The accuracy test from exponential smoothing shows the results EASTMAN-TO2380, PR1782B2, CA1010, and PAINT BRUSH2INCH have better accuracy using single exponential smoothing than holt exponential smoothing.

And then for the unstable demand pattern RENLAM-LY560 + REN-HY560 TS, ARDROX9PR5, FREKOTE700NC, AEROSHEL-FLUID41, AW106, and C25/90S have a better level of accuracy using the Croston, S15/90 and PAINT BRUSH21/2INCH have better accuracy levels by using boylan approximation Syntetos method and LPS3 (00305), BB3100 and AeroshellTurbine Oil 2 have better accuracy rates by using the Teunter Babai Syntetos counter method.

## CONCLUSION

The study classified consumable parts at an aircraft maintenance company using *ABC* analysis, selecting five part numbers each for categories A, B, and C, with category A parts requiring special attention due to their high contribution to total value despite some having small quantities. Subsequent *ADI-CV* analysis of these 15 part numbers revealed that four had a smooth demand pattern, one had an erratic pattern, and ten exhibited a lumpy demand pattern, with no intermittent demand observed. Forecasting accuracy varied by demand pattern: *single exponential smoothing* was most effective for smooth demand, *Croston* for sporadic demand, *Syntetos Boylan Approximation (SBA)* for higher variation in demand frequency, and *Teunter Syntetos Babai (TSB)* for irregular demand with significant activity changes, highlighting the importance of choosing forecasting methods tailored to specific demand characteristics to improve prediction accuracy and supply chain efficiency. For future research, it is recommended to address current limitations by incorporating external factors such as changes in aviation regulations, unscheduled maintenance, and global market dynamics that influence demand patterns. Additionally, combining traditional forecasting methods like *Croston*, *SBA*, and *TSB* with machine learning techniques could better capture complex demand behaviors, and exploring the implementation of *Vendor Managed Inventory (VMI)* systems may further enhance supply chain efficiency by shifting inventory management responsibilities to suppliers based on real consumption data and customer needs.

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