©2022 The 7th International Conference on Management in Emerging Markets (ICMEM 2022)

Paper 48

Spare Parts Inventory Management : A Classification and A Forecast Model In Fertilizer Industry

Riska Aulia and Ratih Dyah Kusumastuti

ICMEM

The 7th International Conference on Management in Emerging Markets

Abstract - **The agricultural sector is crucial for the growth of Indonesia's economy. The fertilizer company, in particular, is an essential part of the agricultural sector, and needs to manage its spare parts inventory to prevent production failures and minimize the company's plant maintenance expenses. This paper presents a fertilizer company's classification and demand forecasting of spare parts. The classification is conducted using a multi-criteria ABC method with Exponential smoothing weighting, which analyzes the trade-offs between the criticality of spare parts and the total inventory value. On the other hand, demand forecasting is carried out using the Croston forecasting model, Syntetos-Boylan Approximation, and Single exponential smoothing. From the 2024 data analysis, the results of the classification of spare part items show significant changes in categories A, B, and C before and after applying the Multi-criteria ABC method. The results also show that the forecasting using the Single Exponential Smoothing model gives lower error than the other two models. The data used are 10 samples of spare part items with indicator A for the period 2016 to 2021.**

Keywords - **Spare parts inventory management; Croston model; multi-criteria ABC; Single Exponential Smoothing; Spare parts forecasting; Syntetos-Boylan Approximation**

I. INTRODUCTION

The reliability of an industrial equipment will decrease in the long term, which means that as the age of use increases, at a certain point the equipment must be maintained or even replaced [1]. One form of equipment maintenance is to replace damaged equipment so that there is no jamming of the old equipment operation. Downsizing of equipment can result in wasted costs, therefore the supply of spare parts (spare parts) for operating equipment is essential. The number of spare parts in a medium scale engineering business may be in the tens of thousands while in a large scale factory it can reach hundreds of thousands, under these conditions it will be difficult to find the right scale control strategy of each spare part using only humans and therefore inventory management becomes a challenge. large [2]. Control of spare parts inventory is playing an increasingly important role in modern operations management. In spare parts inventory management there are trade-offs, on the one hand too large spare parts provide a large number of services, but on the other hand too little inventory results in bad customers or very expensive emergency actions that can result in losses to the company. According to [2] operational support and maintenance costs in industrial plants can reach 60% of the total cost with 25%-30% of the costs related to spare parts so that good spare parts inventory management is needed.

To facilitate the management of spare parts, one of the strategies that can be done is to classify these spare parts into a certain category based on similarities in their features and determine their management strategy. One method that is commonly used is the ABC method. The ABC method has traditionally only focused on one criterion, but over time this method has been modified to be able to classify more than one criterion. Multi-criteria ABC is used to classify a number of items with different criteria. The purpose of this paper is to make an additional contribution to the field of spare part inventory management by classifying it using the multi-criteria ABC method with Exponential Smoothing weighting and doing a forecasting comparison of spare part demand using the Croston, Syntetos-Boylan Approximation, and Single Exponential Smoothing methods. Forecasting the demand for spare parts also presents its own challenges, because the demand for spare parts is intermittent. According to Turini and Meissner [3] the demand for spare parts is generally intermittent, infrequent and can indicate no demand at all (the average length of the interval between requests is large).

We conduct a real-word case study using a dataset acquired from one of a large Fertilizer Plant in Indonesia. This industrial sector was chosen because it plays a direct role in increasing the growth of the agricultural sector. The agricultural sector is a sector that plays an important role in economic growth in Indonesia. Based on data from the Central Statistics Agency (BPS) the agricultural sector continues to contribute to the recovery and national economic growth during the COVID-19 pandemic by contributing 1.35% of 66.42% of GDP (Ministry of Agriculture of the Republic of Indonesia, 2021). This paper is expected to contribute by aiding managers in the fertilizer industry to better manage spare parts by taking into account certain criteria.

II. LITERATURE REVIEW

The review of the relevant literature is divided into three main areas. Section 2.1 introduces operations management and describes maintenance in operations management. Section 2.2 explains the classification of spare parts and the method to be used in our research. In Section 2.3, the forecasting models used in this study are described.

2.1 Operations management

Production is the creation of a good or service, and operations management is a series of activities involved in creating or making a product or service that has added value through changing inputs into outputs [4]. According to the same source, there are 10 strategic operations management decisions, namely: goods and services design, quality management, process strategy, location strategy, layout strategy, human resources, supply chain management, inventory management, scheduling and maintenance [4]. Every manufacturing company carries out the same basic function, namely converting resources into finished goods, and to continue to be able to carry out this function, the company or producer must continue to improve its operational efficiency. One of the decision areas in operations management is maintenance that plays an important part in ensuring that all equipment is always in working order [4]. Maintenance activities requires spare parts for replacement of equipment items that have potential to be damaged or failed. The number of spare parts in a manufacturing company may be hundreds or even thousands of units.

2.2 Spare parts classification

According to [5] there are several ways to classify spare part, but the most common method is the traditional ABC for the quantitative method and the VED for the qualitative method. Reference [6] first proposed the ABC classification method based on Pareto's law and divided spare parts items into three categories A, B and C (generally based on the annual dollar usage criteria). Meanwhile, VED method segment the item of spare parts into three segmentation (Vital, Essential, and Desirable) to facilitate analysis and decision making [7]. Reference [8][9] said in their research that the ABC method allows differentiated management of each class. Recent studies have expanded the criteria in the use of this ABC method [10], emphasize the role of lead time criterion in analyzing the competitiveness of companies [11][12] put the criticality as the other criterion. In this paper we use three criteria for spare parts classification, namely, annual dollar usage, number of hits, and average dollar per hits.

2.3 Spare parts demand forecasting

Spare parts forecasting is divided into parametrics and non-parametric approaches, where parametric methods are typically rely on bootstrapping procedure that directly evaluates the percentiles of the distribution from data [3]. Some studies from [13][14][15]have been shown that these methods have advantages in certain situations but they are not well received by practitioners, because they are computationally demanding and increase the complexity of the calculation. The most classic estimation method is exponential smoothing, but then in 1972 Croston demonstrates that this method is biased in the presence of intermittent demand, which is the very common characteristic of spare parts, and he introduces the first estimation method that directly addresses the intermittency of the data [16]. However, the study by Syntetos and Boylan [17] introduced the new estimation method that corrected for the bias in the Croston's method.

III. METHODOLOGY

The object of this research is a fertilizer company in Indonesia. The research methods used in this study are as follows:

3.1 Spare parts classification

The classification of inventory into the A, B, or C categories have generally been based on dollar value per unit multiplied by annual usage rate, commonly known as dollar usage. In this paper, we apply a classification model using the Multi-criteria ABC method with Exponential Smoothing Weights proposed by [18] with the selected criteria as follows:

- Annual dollar Usage, or the annual fee
- Number of hits, or the number of items used
- Average Value per hit, or an overview of the average dollar value for each transaction for an item and the loss incurred in the event of a shortage.

Hence, with the above criteria, calculations are carried out using the following equation:

Average value per hit = Annual dollar usage / number of hits (3.1)

The results of the calculations were then standardized with the following equation:

$$\text{Standardized Value} = N_{ij} / L_i \qquad (3.2)$$

where:
N_{ij} = Item j in criterion i
Li = Largest value in criterion i
for i = number of criteria, dan j = number of items

after standardization, the next step is the determination of Exponential Smoothing Weights. Determination of exponential smoothing weights is used when decision makers want to assign different weights or values to criteria with the following equation:

$$\text{Weight} = \alpha\,(1-\alpha)^{n-1} \tag{3.3}$$

where: $(0 \leq \alpha \leq 1)$ and n = number of criteria

3.2 Spare part forecasting

One of the basic requirements of spare part management is forecasting of spare part demand. Because of its characteristics, that is very difficult to forecast demand accurately. Forecasting spare parts has a different nature where there is an intermittent/lumpy demand pattern, or it can be called as an intermittent demand pattern, so that the forecasting used is different from forecasting demand for a product in general. In this paper, after the classification, 10 samples with the highest weight or category A will be forecasted. The forecasting models that will be used are Single Exponential Smoothing model, Croston's model, and Syntetos-Boylan Approximation model, which are the common model used for forecasting intermittent demand.

A. Single Exponential Smoothing

In the Single Exponential Smoothing (SES) method, the first step that must be done is to calculate the initial level with the equation in [19] namely:

$$L_0 = \frac{1}{n}\sum_{i=1}^{n} Di \tag{3.4}$$

Where:
L_0 = Initial level
D_i = Demand or demand in period i

The initial level formula is used as the average value of demand over the entire period, and this formula is used at the time of forecasting for the next forecasting, the following formula is used:

$$L_{t+1} = \alpha D_{t+1} + (1-\alpha)L_t \tag{3.5}$$

Where:
$L_{(t+1)}$ = Level in period t+1
α = Smoothing constant (Alpha)
D_t = Demand or demand in period
L_t = Level in period t

B. Croston's method

Croston's forecasting method is divided into two parts, which consist of updated demand (Zt) and demand interval (Pt). In period t, if there is demand in that period, the demand forecast and the inter-arrival time, namely t, zt, and pt, do not change or the value remains the same as the previous value. If in that period there is a demand then Xt > 0, and the forecasting calculation changes to.

$$z_t = \begin{cases} z_{t-1}, if\ X_t = 0 \\ \alpha\,.X_t + (1-\alpha)\widehat{z_t},\ if\ X_t > 0 \end{cases} \tag{3.6}$$

$$q_t = \begin{cases} q_{t-1} + 1, jika\ X_t = 0 \\ 1, jika\ X_t > 0 \end{cases} \tag{3.7}$$

$$z_t = \begin{cases} p_{t-1}, if\ X_t = 0 \\ \alpha\,.q_{t-1} + (1-\alpha).p_{t-1}, if\ X_t > 0 \end{cases} \tag{3.8}$$

From the above equation, an update for the Croston formula is obtained with the following equation:

$$Y_t = \frac{z_t}{p_t} \tag{3.9}$$

Where:
Yt = Value of forecasting projection in the next period
zt = Forecasting size value based on actual demand data
pt = Forecasting interval value based on actual demand data
α = Smoothing constant with value 0 < < 1.

C. Syntetos-Boylan Approximation Method

The Croston's forecasting method shows that there is a bias. And to overcome this, Syntetos and Boylan also provide a new equation to correct the bias by adding a correction factor in the form of 1-/2 and the equation finally turns into the following equation:

$$Y_t = (1-\frac{\alpha}{2})\,\frac{z_t}{p_t} \tag{3.10}$$

Where:
Yt = Value of forecasting projection in the next period
zt = Forecasting size value based on initial request data
pt = Forecasting interval value based on actual demand data
α = smoothing constant (Alpha)

The calculations of demand size (zt) and demand interval (pt) follow the equation in the Croston forecast (equation 3.6 – 3.8). For the formula for the first alpha constant, you can use the formula proposed by [20] as follows:

$$\alpha = 2\ (n+1) \tag{3.11}$$

Where:
α= Smoothing constant (alpha)
n= Number of periods of historical data used for forecasting

D. Forecasting Accuracy

1. Mean Absolute Deviation (MAD)

The first measurement of error is the mean absolute deviation (MAD). This value is calculated by adding up the absolute value of the individual forecasting errors (deviations) and dividing by the number of data periods, as in the following formula [4]:

$$MAD_n = \frac{\Sigma|A_t - F_t|}{n} \quad (3.12)$$

Where:

$A(_t)$ = Actual Request

F_t = Demand forecast

n = Number of data periods

2. Mean Square Error (MSE)

Mean squared error (MSE) is a second way to measure the overall forecast error. MSE is the average of the squared differences between the estimated and observed values [4] with the following formula:

$$MSE = \frac{\Sigma(A_t - F_t)^2}{n} \quad (3.13)$$

Where:

$A(_t)$ = Actual Request

F_t = Demand forecast

n = Number of data periods

3. Mean Absolute Percent Error (MAPE)

The problem with MAD and MSE is that their value depends on the size of the forecasted item, if the forecast item is measured in thousands, the MAD and MSE value can be very large [4]. To avoid this problem, we can use Mean Absolute Percent Error (MAPE). It is calculated as the average of the absolute difference between the estimated value and the actual value, expressed as a percentage of the actual value, meaning that if we have an estimate and an actual value for n periods, the MAPE is calculated as follows [4]:

$$MAPE = \frac{\sum_{i=1}^{n} 100|A_i - F_i|/A_i}{n} \quad (3.14)$$

Where:

$A(_t)$ = Actual Request

F_t = Demand forecast

n = Number of data periods

selection of the best forecasting method based on its MAD, MSE, and MAPE value. The demand forecasting method with the smallest value is the best method.

IV. FINDINGS AND DISCUSSION

There are 2024 spare part items that will be grouped in this study. These spare part items are movable spare part items or there is at least one transaction within a period of five years. Furthermore, the 2024 spare part items are classified using the multi-criteria ABC method based on the weights calculated using the Exponential Smoothing weighting equation. The spare parts items that have an accumulated weight of 70% of the overall weight fall into category A, and spare parts items which has an accumulated weight of 20% of the overall weight is in category B, and finally spare parts items that have an accumulated weight of 10% of the total weight are included in category C. The comparisons of classification between before and after the application is presented in Table I.

Table 1 - Number of Spare Part Items in Each Category Before and After Classification using the Multi-criteria ABC method

ABC Indicator	Before	After
A	1024	147
B	528	486
C	23	1391

Forecasting in this study aims to see the demand for spare parts items with indicator A. We compare three methods to find the best forecasting method for this case. The data used for forecasting is the historical data on demand/use of spare parts in the period 2016 to 2021, with a smoothing constant or of 0.3 for each forecasting model.

The Single Exponential Smoothing method is used to forecast spare parts items because this method is good for use on demand that does not have a trend or seasonality [19]. In forecasting using the Single Exponential Smoothing method, the forecasting results tend to follow the pattern of actual demand. In forecasting using the Croston method, the forecasting calculation is divided into two parts, namely the part with a zero value and a non-zero value.

The Croston forecasting method gives results that are much different from forecasting with the previous Single Exponential Smoothing model. In this forecasting model, it appears that the forecasting results show a tendency for horizontal demand patterns where the forecasting results fluctuate around the average value. The Croston's model is a forecasting model adapted from the Single Exponential Smoothing forecasting model, but in Croston's model the projection for data with a zero value follows the previous projection data and updates the calculation when the data is no longer zero. However, in this study, it is shown that the demand forecasting pattern of the Single Exponential Smoothing and Croston models are very different.

The Syntetos-Boylan Approximation forecasting model is the result of a modified Croston's forecasting model, where this model reduces bias by adding a correction. Forecasting generated from the Syntetos-Boylan Approximation model is similar to the projections of the Croston model (see Figures 1 to 10).

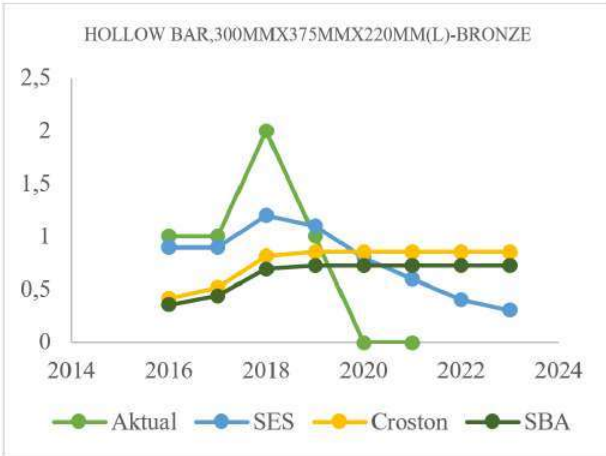

Fig. 1. Comparisons of actual demand and forecasting results using the Single Exonential Smoothing model, Croston model, and Syntetos-Boylan Approximation model on HOLLOW BAR, 300MMX375MMX220MM (L)-BRONZE.

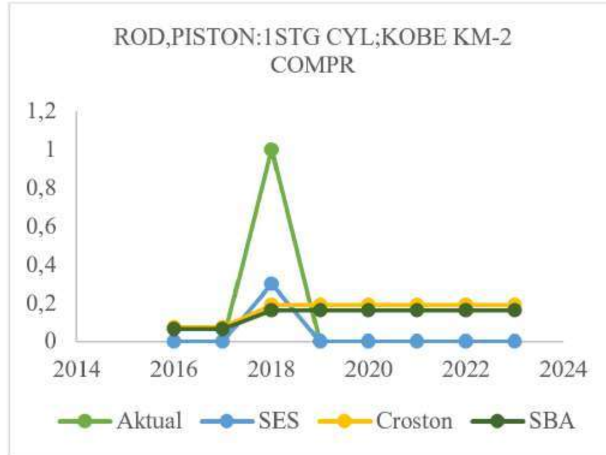

Fig. 4. Comparisons of actual demand and forecasting results using the Single Exponential Smoothing model, Croston's, and Syntetos-Boylan Approximation model on ROD,PISTON:1STG CYL;KOBE KM-2 COMPR

Fig. 2. Comparisons of actual demand and forecasting results using the Single Exonential Smoothing model, Croston model, and Syntetos-Boylan Approximation model on CHAIN ASSY,ROLLER

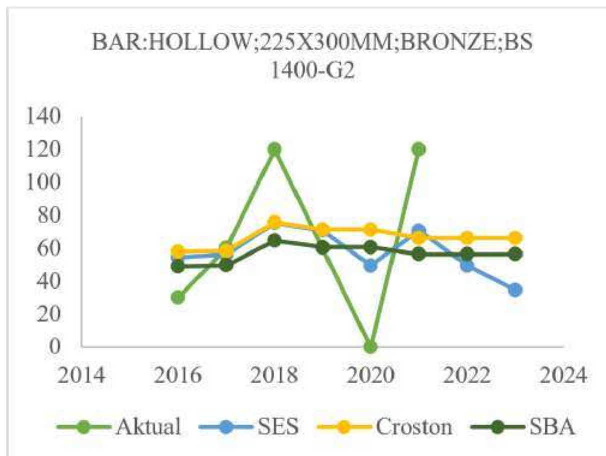

Fig. 5. Comparisons of actual demand and forecasting results using the Single Exponential Smoothing model, Croston's model, and Syntetos-Boylan Approximation model on BAR: HOLLOW; 225X300MM; BRONZE; BS 1400-G2

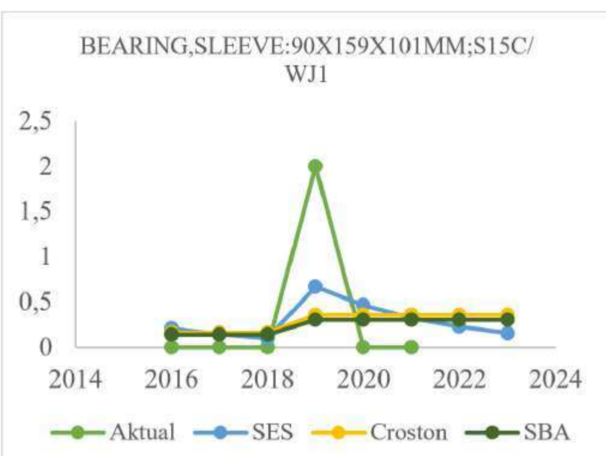

Fig. 3. Comparisons of actual demand and forecasting results using the Single Exponential Smoothing model, Croston's model, and Syntetos-Boylan Approximation model on BEARING, SLEEVE: 90X159X101MM;S15C/WJ1

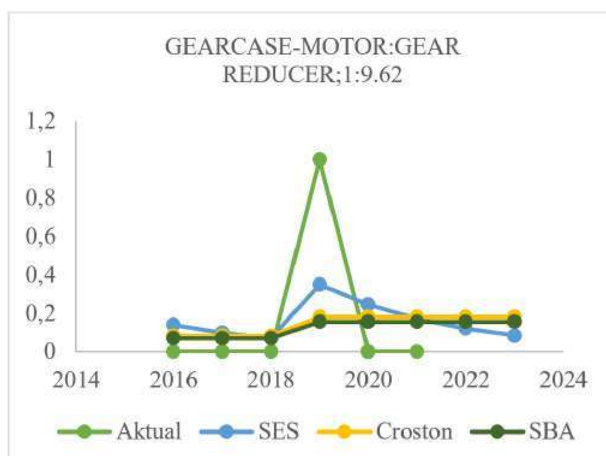

Fig. 6. Comparisons of actual demand and forecasting results using the Single Exponential Smoothing model, Croston's model, and Syntetos-Boylan Approximation model on GEARCASE-MOTOR: GEAR REDUCER; 1:9.62

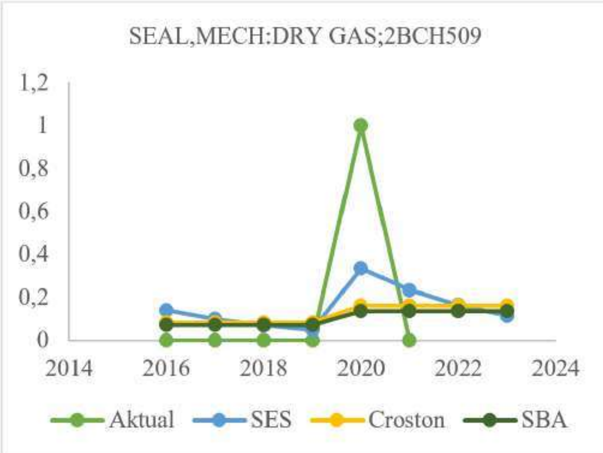

Fig. 7. Comparisons of actual demand and forecasting results using the Single Exponential Smoothing model, Croston's model, and Syntetos-Boylan Approximation model on SEAL,MECH: DRY GAS; 2BCH509

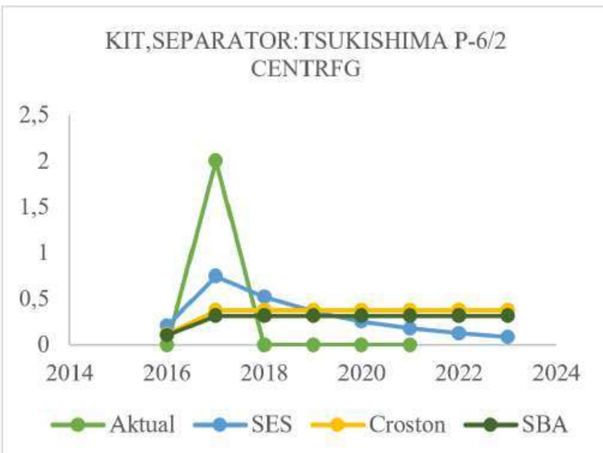

Fig. 8. Comparisons of actual demand and forecasting results using the Single Exponential Smoothing model, Croston's model, and Syntetos-Boylan Approximation model on KIT,SEPARATOR: TSUKISHIMA P-6/2 CENTRFG

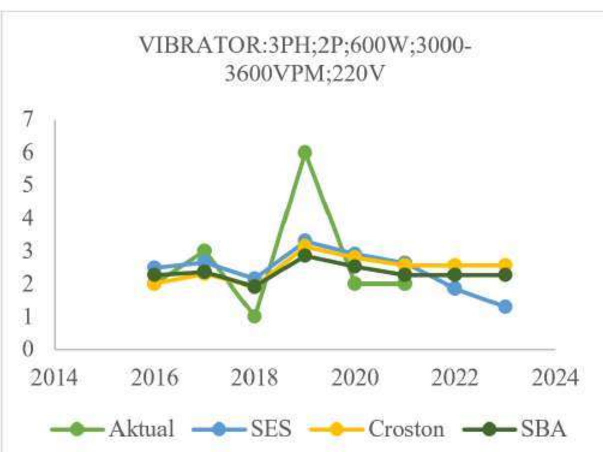

Fig. 9. Comparisons of actual demand and forecasting results using the Single Exponential Smoothing model, Croston's model, and Syntetos-Boylan Approximation model on VIBRATOR: 3PH; 2P; 600W; 3000-3600 VPM; 220V

Fig. 10. Comparison of actual demand and forecasting results using the Single Exponential Smoothing model, Croston's model, and Syntetos-Boylan Approximation model on RING,PISTON:KOBE KM-2 COMPR

Table II presents the comparison results of the accuracy of three forecasting models. It can be seen that the forecasting model that gives the smallest MAD and MSE value is Single Exponential Smoothing model, followed by the Syntetos-Boylan Approximation model, and finally the Croston's model. For the MAPE value Croston's model give the smallest value followed by Single Exponential Smoothing model, and the Syntetos-Boylan Approximation model.

V. CONCLUSION

ABC classification method is the most commonly used method in spare parts inventory management. The multi-criteria ABC method with exponential smoothing weighting provides convenience in application in the real world and still provides significant values on criteria that are considered important as a classification reference. research on [21] [22] also uses the multi-criteria ABC method as the basic method of classification. they also combine it with several other classification models. Not always items with high prices are on indicator "A", and conversely, not all items with low prices are on indicator "C". with more criteria taken into account will provide a better assessment for the placement of categories of each spare parts item.

In forecasting the spare part items, the single exponential smoothing model gives the best forecasting results because the error value of this forecasting result is smaller than the other two models. research on [23][24] demand data patterns that do not show any indication of seasonality or trend using the Single Exponential Smoothing forecasting model

This study is not without limitations, the use of criteria in this study is still very limited to only three criteria. for further research, to provide the right classification, other criteria can be added, such as obsolescence, lead time, and others. Another limitation of this study is the use of data that is limited to six periods. Further research can add the period used in order to get a more accurate forecast.

ACKNOWLEDGMENT

The authors extend their sincere thanks to the local manufacturing enterprise for supporting the proposed research by sharing and providing dataset. In addition, the authors would like to thank the anonymous experts who helped developing and improving the proposed model.

Table 2 - MSE-Based Forecasting Accuracy Calculation Results

Material Number	Material Description	MAD			MSE			MAPE		
		SES	CROSTON	SBA	SES	CROSTON	SBA	SES	CROSTON	SBA
6141040	HOLLOW BAR,300MMX375MMX220MM(L)-BRONZE	0,42	0,73	0,71	0,28	0,62	0,58	11,67	22,46	26,59
6142491	BEARING,SLEEVE:90X159X101MM;S15C/WJ1	0,43	0,45	0,42	0,36	0,41	0,41	11,07	10,24	10,58
6136261	CHAIN ASSY,ROLLER	18,69	21,17	19,94	432,99	540,34	527,94	17,97	16,06	17,40
6139710	ROD,PISTON:1STG CYL;KOBE KM-2 COMPR	0,12	0,24	0,22	0,08	0,11	0,11	11,67	10,11	10,46
6140778	GEARCASE-MOTOR:GEAR REDUCER;1:9.62	0,23	0,22	0,21	0,09	0,10	0,10	10,87	10,24	10,58
6137072	SEAL,MECH:DRY GAS;2BCH509	0,21	0,21	0,19	0,09	0,10	0,10	11,11	10,50	10,80
6143106	KIT,SEPARATOR:TSUKISHIMA P-6/2 CENTRFG	0,46	0,50	0,46	0,35	0,44	0,43	10,44	10,16	10,51
6134883	BAR:HOLLOW;225X300MM;BRONZE;BS 1400-G2	30,43	42,78	40,30	1268,86	2448,52	2202,72	30,72	24,46	22,67
6146408	VIBRATOR:3PH;2P;600W;3000-3600VPM;220V	1,04	1,37	1,28	1,70	2,94	2,72	32,72	28,71	27,06
6138950	RING,PISTON:KOBE KM-2 COMPR	2,48	3,25	3,04	8,93	13,41	12,68	11,43	13,90	15,57
	Average	**5,452**	**7,091**	**6,679**	**171,373**	**300,698**	**274,780**	**15,966**	**15,682**	**16,220**

REFERENCES

1. C. Jackson & R. Pascual, "Optimal maintenance service contract negotiation with aging equipment." European Journal of Operational Research, 387-389, 2018.

2. Q. Hu, S. Chakhar, S. Siraj, & A. Labib, "Spare parts classification in industrial manufacturing using the dominance-based rough set approach." European Journal of Operational Research, 262, 1136-1163, 2017.

3. L. Turrini and J. Meissner, "Spare parts inventory management: New evidence from distribution fitting" European Journal of Operation Research, 273, 118-130, 2019.

4. J. Heizer, B. Render, & C. Munson, Operations Management, 13th Ed. Global Edition. England: Pearson Education, 2020.

5. I. Roda, M. Macchi, & L. Fumagalli, "A review of multi-criteria classification of spare parts", Journal of Manufacturing Technology Management, Vol. 25 No. 4, pp. 528-549, 2014.

6. Partovi, F. Y., & Burton, J. (1993). Using the analytic hierarchy process for ABC anal- ysis. International Journal of Operations & Production Management, 13 (9), 29–44.

7. R. Botter, and L. Fortuin, "Stocking strategy for service parts – a case study", International Journal of Operations and Production Management, Vol. 20 No. 6, pp. 656-674, 2000.

8. A. Bacchetti, and N. Saccani, "Spare parts classification and demand forecasting for stock control: investigating the gap between research and practice", Omega, Vol. 40 No. 6, pp. 722-737, 2012.

9. J. Stoll, R. Kopf, J. Schneider, & G. Lanza, "Criticality analysis of spare parts management: a multi-criteria classification regarding a cross-plant central warehouse strategy", Production Engineering, Vol. 9 No. 2, pp. 225-235, 2015.

10. S. de Treville, I. Bicer, V. Chavez-Demoulin, V. Hagspiel, N. Schürhoff, C. Tasserit, et al., Valuing lead time. Journal of Operations Management, 32 (6), 2014.

11. Exton, T., & Labib, A. (2002). Spare parts decision analysis—The missing link in CMMS's (Part II). Journal of Maintenance & Asset Management, 17 (1), 14–21.

12. Ghaddar, B., Sakr, N., & Asiedu, Y. "Spare parts stocking analysis using genetic programming", European Journal of Operational Research, 252 (1), 2016.

13. J. H. Bookbinder, & A. E. Lordahl, "Estimation of inventory re-order levels using the bootstrap statistical

procedure", IIE Transactions, 21 (4), 302-312, 1989.

14. T. R. Willemain, C. N. Smart, & H. F. Schwarz, "A new approach to forecasting intermittent demand for service parts inventories", International Journal of Forecasting, 20, 375-387, 2004.

15. E. Porras, & R. Dekker, "An inventory control system for spare parts at a refinery: An empirical comparison of different re-order point methods", European Journal of Operational Research, 184, 101-132, 2008.

16. J. D. Croston, "Forecasting and stock control for intermittent demands", Operational Research Quarterly, 23(3): 289-303, 1972.

17. A. A. Syntetos, & J. E. Boylan, "The accuracy of intermittent demand estimates", International Journal of Forecasting, 21 (2), 303-314, 2005.

18. H. Jamshidi, & A. Jain, "Multi-criteria ABC inventory classification: With exponential smoothing weights", Journal of Global Business Issues, 2 (1), 61-67, 2008.

19. S. Chopra, & P. Meindl, "Supply chain management. Strategy, planning & operation", In Das Summa Summarum des Management, Gabler, 2007.

20. F. R. Jacobs, & R. B. Chase, "operations and supply chain management", Bershire: McGraww-Hill education, 2014.

21. J. Liu, X. Liao, W. Zhao, & N. Yang, "A classification approach based on the outranking model for multiple criteria ABC analysis", Omega, (61), 2016.

22. A. Hadi-Vencheh, " An improvement to multiple criteria ABC inventory classification", European Journal of Operational Research, 201, 2010.

23. W. Romeijnders, R. Teunter, & W. Van Jaarsveld, "A two-step method for forecasting spare parts demand using information on component repairs", European Journal of Operation Research, 220, 386-393, 2012.

24. R.H. Teunter, & L. Duncan, "Forecasting intermittent demand: a comparative study", European Journal of Operation Research 60, 321-329, 2009.