Comparison of ARIMA, *Linear Trend* and *Single Exponential Smoothing* for short-term forecasting of power plant spare parts inventory

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Abstract

Spare parts are one of the keys to the success of a power plant company to achieve a world-class company. The method of forecasting required for the control and cost of the gas turbine type power plant spare parts. The purpose of this study is to model demand using the ARIMA method, linear trend, and single exponential smoothing for short-term forecasting of gas turbine power plant spare parts. Forecasting the demand for spare parts in the power generation industry is carried out using real and accurate data on the level of demand for spare parts for 3 years. The results of the analysis show that the ARIMA model provides the most accurate level of forecasting with the right MAPE value and helps provide an overview of the optimal spare parts procurement process in the short term.

Keywords: spare parts, forecasting, ARIMA, trends linier, single exponential smoothing.

1. Introduction

In the development of a country supported by the important role of the electricity sector. Its role is not only limited as a means of production to facilitate the development of other economic sectors (such as processing industry, agriculture, mining, education, and health), but also as a factor that can meet the social needs of everyday people (Adam, 2016). Based on (Arief, 2011) and (Adam, 2016) it can be concluded that electricity as a base sector that becomes the foundation for achieving development goals, such as creating job opportunities, increasing national income, changing economic structure, and improving people's welfare.

The industrial era 4.0 has now penetrated to all lines, from the financial sector to power plants as previously described. Competition between companies is getting tighter and demands operational efficiency must be done to maximize profits. In supporting these efforts several factors support, one of which is smooth production. The smooth production process in the power generation sector is important in providing reliable services. The company's efforts in supporting the process are the maximum maintenance of power plant facilities. This aims to make the power plant function following its capacity. In the process of repair always need spare parts repair, but the willingness of parts to be part is very important so as not to occur overstock and waiting parts. Based on the company's Annual report in 2018, the company's total assets reached 18.96 trillion rupiahs. Wherefrom the financial side of the balance sheet, the inventory of spare parts in the warehouse presents 20% to 60% of the total assets. If the inventory is converted and used into cash, it can affect cash flow and return on investment.

Meanwhile, the availability of spare parts is one of the keys to the success of a power generation company to achieve a world-class company. Forecasting in demand for spare parts is critical in controlling parts inventory and avoiding high parts shortages and parts storage costs (Zhu et al., 2020). This is done in an effort to avoid shortages of spare parts in particular for the problem of demand for parts that are not fixed to rarely used parts (Petropoulos & Kourentzes, 2015).

Based on the research (Zhu et al., 2020) added that the lack of inventory of spare parts in meeting the needs can reduce the level of customer satisfaction. Uncertainty in demand for spare parts can make parts inventory control systems increasingly difficult (Kennedy et al., 2002). Inventory Turn Over serves to know how quickly a product or item flows relative to the average amount stored in inventory control. (Trisnawati et al., 2018). Currently, inventory concept tends to use zero inventory policy but still difficult to realize (Liu et al., 2019). Based on previous research, there needs to be an efficient and effective process of controlling the supply of spare parts in gas turbine power plant units in an effort to improve the inventory control system of these parts.

2. Literature Review

Over the past 50 years, forecasting and planning for inventory management have received considerable attention due to their implications for decision-making (Syntetos et al., 2009). An important issue for successful inventory organizations is accurate demand forecasting, as demand distribution during lead time is used to determine the number of replenishment orders and rearrange points (Dolgui et al., 2017). In most common conditions, the appropriate forecasting method is exponential smoothing and moving average (Snyder, 2001). Forecasting demand leads to the tricky lead time for slow-moving items. First, demand for parts is often disjointed, meaning that random requests have a large proportion of zero values (Croston, 1972). Second, historical data on parts demand is usually limited due to high turnover rates. In 1972, Croston first discovered that traditional forecasting methods such as moving averages and exponential smoothing could lead to sub-optimal stocking decisions indicating that this method may not be appropriate for slow-moving items, and he proposed another traditional forecasting method called the single Croston method (CR) that takes into account the size of demand and the time between arrivals between requests. The CR method has been estimated by some authors since 1972 and most researchers conclude that the CR method is more suitable for intermittent demand than traditional methods. Forecasting, in general, is a difficult task, but perhaps more challenging for developing countries. This is mainly because developing countries are more likely to experience various structural changes than developed countries, so an accurate sales forecasting system is an efficient way to address them (Aye et al., 2014).

3. Methods

3.1. Autoregressive Integrated Moving Average

To model the time series, we can use traditional statistical models, including moving averages, exponential smoothing, and ARIMA. This model is linear because the narrower future value becomes a linear function than the previous data. In recent decades, your researchers have proven that they pay close attention to linear models that are easy to understand and apply. One of the well-known methods used in estimating time-series data is ARIMA. The ARIMA method is used to analyze time-series data in which it is designed by integrating AR (autoregressive) and MA (moving average) methods. ARIMA (p, d, q) is a common method formulated against only stationary data series, where, p is the number of processes in AR, d is the different amount of time series data becomes stationary, and finally, q is the number of processes in MA. According to the Box-Jenkins methodology (Box et al., 2008), there are four approximate stages, which include; (Energy et al., 2019). Identification model; the data series will be carefully examined to determine if it contains random trends, seasonality, cycles, or phenomena. After that, ACF and PACF samples from the original series are calculated and examined to further confirm that the time series data is stationary. If the ACF sample swoops very slowly, it indicates that a difference is required process, (Alfred et al., 2018) parameter estimation; the purpose of model validation is to ensure that the right model is used. In this study, it can be done using t-statistic and p-value, (Yusof et al., 2010) model checking; models whose purposes need to be hypothesized and have diagnostic tests before they can be used for forecasting. In this test, we examined based on $p > 0.05$, and (Valipour et al., 2013) estimates; estimated values within the trust limit (upper and lower limits) provide a 95% confidence interval. In this study, we used trial and error methods to get good models and predictions.

3.2. Trends Linier

To do accurate and good forecasting, a variety of data and information are needed and can be observed in a relatively long time, so that from the results of the analysis obtained an idea of how big fluctuations occur and what factors influence the changes in forecasting. Based on scientific studies, the most decisive time series analysis is the accuracy of the information or data obtained and the time or period of the data collected. If the data collected is more and more then the better the estimated forecasting obtained from the results of the study. On the contrary, if the data collected is less then the estimated results of the forecast will be obtained worse. In the least Square Method (MLS): The methods used in time series analysis are Semi Average Method, Free Hand Method, Moving Average Method, and Least Square Method. In this case, it is more focused on analyzing the time series with the smallest squares method that will be divided into two cases, namely even data cases and odd data cases. In general, time series analysis has the following linear line equations: Y = a + b X. Description: Y is the variable that the trend value is looking for and X is the time variable that affects forecasting. As for looking for constant values (a) and parameters (b) as follows:

a = ΣY / N…………….……....... (1)

b = ΣXY / ΣX2……………..…… (2)

Through the Trend linear analysis method can be obtained forecasting equations such as to request function for time series. Known request equations as follows:

$y_{\dot{t}} = a + b$…………….…….... (3)

With values a and b obtained from the formula:

$a = \frac{\Sigma y}{n}$ ………………….…… (4)

$b = \frac{\Sigma tY}{t^2}$ …………………..……… (5)

3.3. Single Exponential Smoothing

The single exponential smoothing method is a method of displaying the weight of the value decreases exponentially with the increasing value of old observations. It's more valuable just given the weight, the weight is relatively greater than the old observations. This method provides an exponential weighting for the moving average of all previous observation values. This way is not affected by trends or seasons.

Calculated as follows:

t+1 = Yt + (1-) t ....(6)

Description:

t+1 = forecast value for the next period

Y_t = request for period t

t = forecasting value for period t

1 = fine-tuning weighting factor (0 < 1)

In formula (6), to predict the value of the next period required to request data from the previous period and forecasting the previous period. Previous observations. This way is not affected by trends or seasons. Index improvement is a weighted moving average forecasting technique in which data is measured by exponential functions (Montgomery et al., 1990) A single exponential smoothing method (SES) is a method of data smoothing by giving more weight to newer data. This method provides geometrically reduced weight for longer observations. By using this technique, data can be refined by eliminating irregular components in the data (Makridakis et al., 1999).

3.4. Data Collection

In this article, the estimated demand for spare parts in the power generation industry is carried out with real and accurate data from the level of spare parts needs for 3 years. This study examines the effectiveness of estimated parts needs for the next year, accuracy and characteristics of research. This study examines the validity of forecast demand for spare parts in the power generation industry.

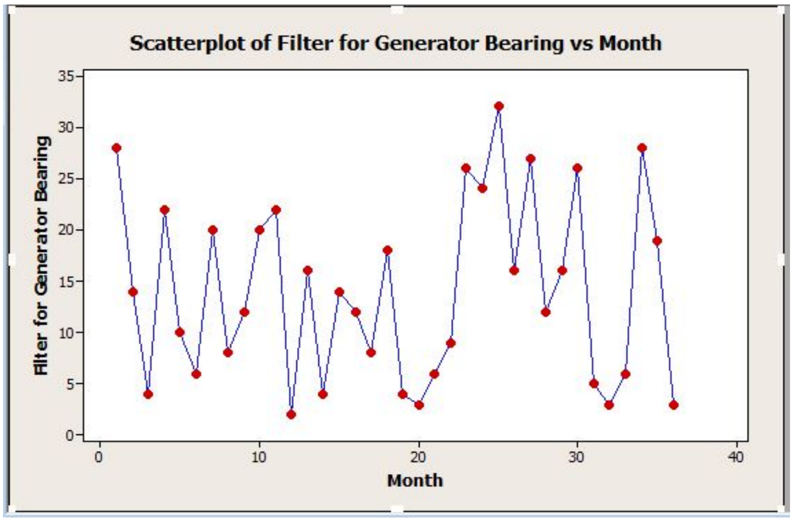

Figure 1. Scatterplot usage historical data.

4. Results and Discussion

4.1 Analysis using ARIMA

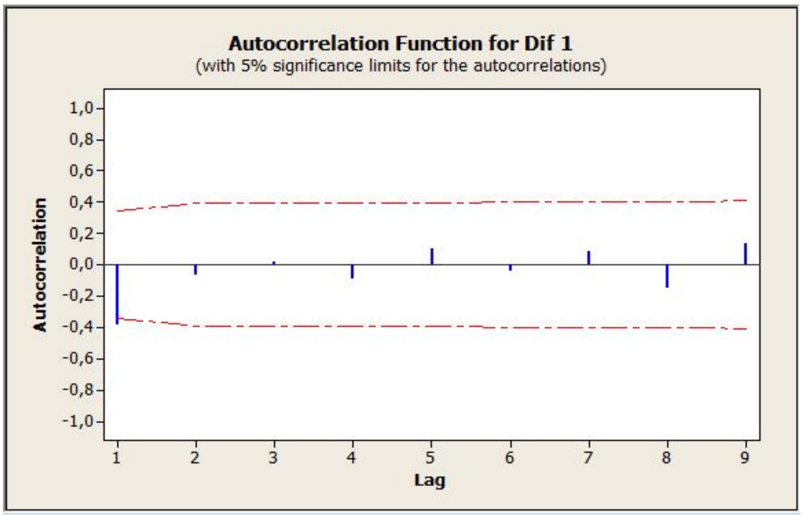

Figure 2. ACF diagram of the request for spare parts

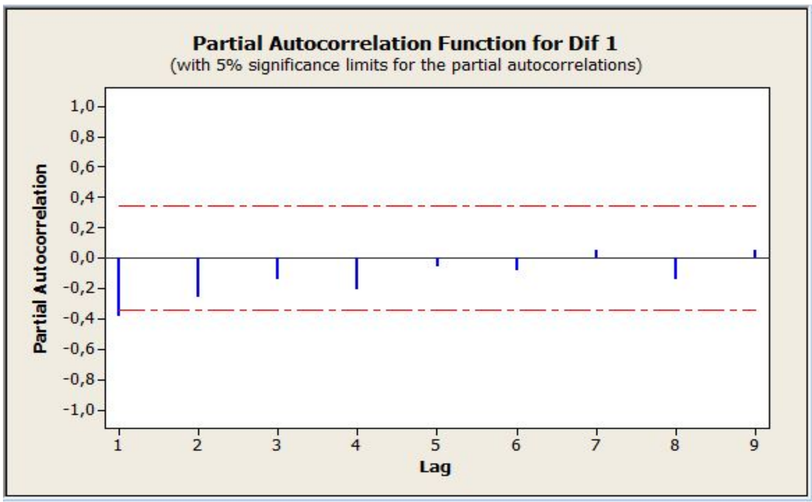

Figure 3. PACF diagram of the request for spare parts

Based on the plot of ACF and PACF, shown in Figure 2. The ACF chart instantly cuts off in lag to the first, while in Figure 3. PACF charts look dying down. If ACF shows a cut off pattern and PACF shows dying down, then it can be said that the ARIMA model is pure MA. It has been identified that the appropriate model for demand size data differencing 1 time is ma model (1) and if returned to the initial data then the demand size data follows ARIMA (0,1,1) and ARIMA (1,1,1).

Table 1. ARIMA Coefficient (0,1,1)

Type	Coef	SE	Coef	T	P
MA	1	0,9662	0,1027	9,41	0,000
Constant		0,0525	0,1494	0,35	0,727
Lag		12	24	36	48
Chi-Square		4,9	22	*	*
DF		10	22	*	*
P-Value		0,901	0,913	*	*

Table 2. ARIMA Coefficient (1,1,1)

Type	Coef	SE	Coef	T	P
AR	1	0,0534	0,1904	0,28	0,781
MA	1	0,9611	0,1143	8,41	0,000
Constant		0,0371	0,1456	0,25	0,800
Lag		12	24	36	48
Chi-Square		4,3	14,2	*	*
DF		9	21	*	*
P-Value		0,890	0,862	*	*

From the estimated results shown in Table 3, it can be seen that the Ljung Box test on the ARIMA model (0,1,1),(1,1,1) has a P-value value of > 0.05 on both legs. This means that this model has fulfilled the assumption of white noise that residual is already random. This model is the simplest, because if the AR and MA values are raised the model cannot be estimated.

4.2 Analysis using Trend Analysis

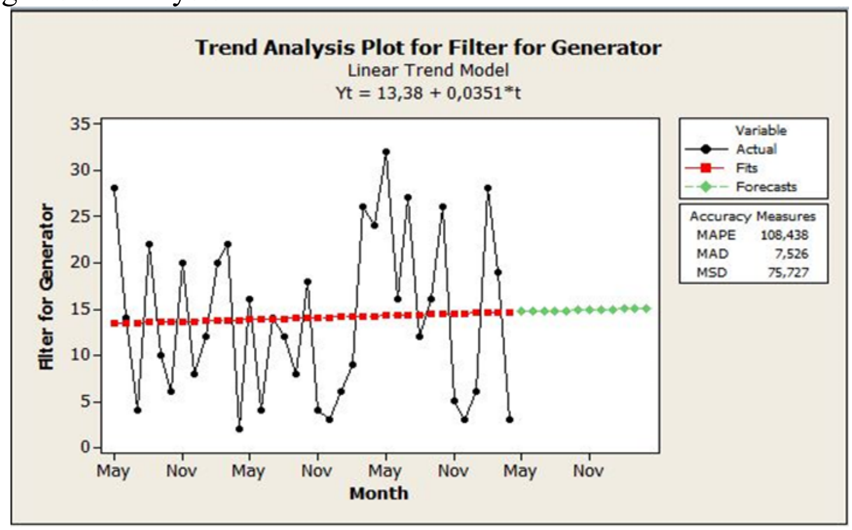

Figure 4. Forecasting Trends Analysis

Figure 4 is a forecast graph of Filter for Generator Bearing J85 with the method used is Trend analysis. The black line shows the actual data of J85 Filter for Generator Bearing product demand, while the red line shows the result of fitting from Trend analysis method. So that in the calculation of forecasting Trend analysis produces the value MAPE = 108,438 MAD value = 7,526 MSD value = 75,727.

4.3 Single Exponential Smoothing

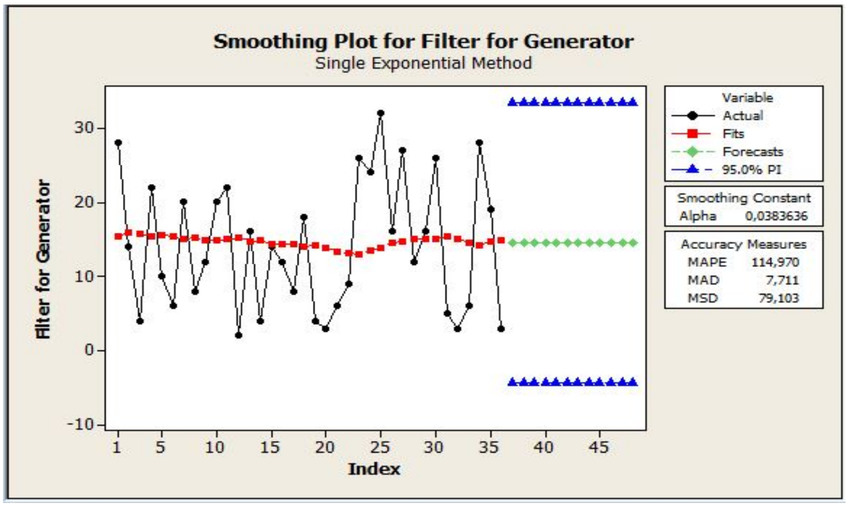

Figure 5. Single Exponential Smoothing Forecasting

Figure 5 is a forecasting graph of Filter for Generator Bearing J85 with the method used is single exponential smoothing. The black line shows the actual data of the J85 Filter for Generator Bearing product demand, while the red line shows the result of the fitting of the single exponential smoothing method. So that in the calculation of single exponential smoothing forecasting produces MAPE value = 114.970 MAD value = 7.711 MSD value = 79.103.

Results to be able to see the accuracy capability of forecasting a model is necessary compared to the observation value of variables with the values obtained from the simulation. This is done ex-post forecasting where the static value to be used to measure the size of the model error is by looking at the RMSE value as an error-slinging parameter. The smallest RMSE value is considered the most optimal in forecasting results that are close to accurate values. The results of calculating the values of accuracy can be seen in Table 3.

Table 3. Comparison of values from different forecasting models

Model	Analysis results	Filter Generator
Trend Analysis	MAPE	108,438
	MAD	7,526
	MSD	75,727
	RMSE	8,702
Single Exponential Smoothing	MAPE	114,97
	MAD	7,711
	MSD	79,103
	RMSE	8,894
ARIMA	MAPE	**0,052**
	MAD	8,41
	MSD	212,08
	RMSE	14,56

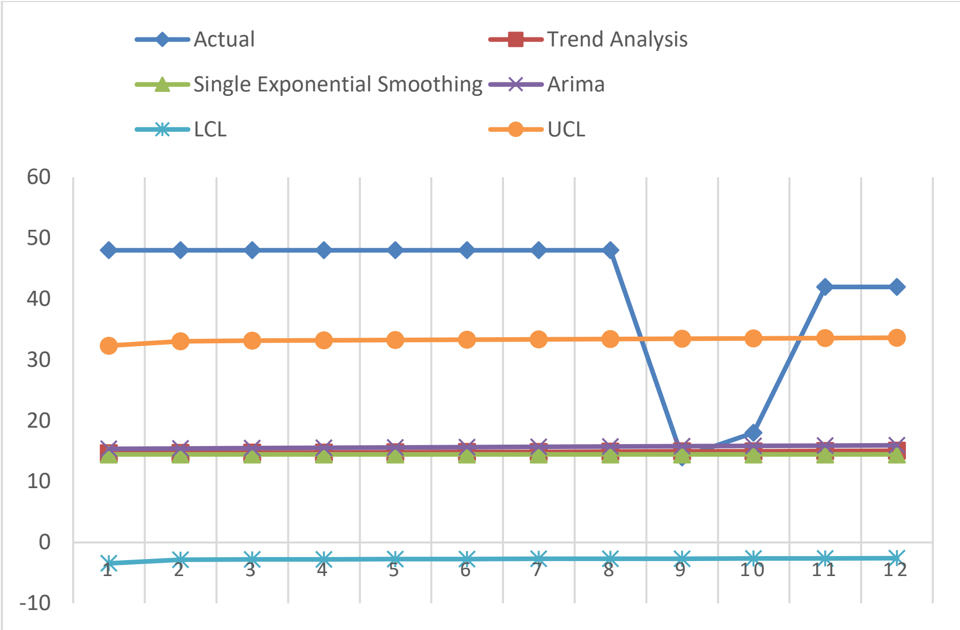

Figure 6. Comparison of plot forecasting demand for spare parts using Arima method, Trend analysis and SES

5 Conclusion

This paper compares learning performance (ARIMA, Trend analysis, and Single Exponential Smoothing) forecasting statistics in time series data. The average of squared errors is to calculate each model and compare. Based on the results obtained, found ARIMA more efficient than Trend analysis and Single Exponential Smoothing in modeling time-series datasets, and modeling time-series datasets related to the total demand for power plant engine parts. With MAPE value of 0.052 which is the amount of error resulting from forecasting. The more accurate MAPE value is in the forecasting process (ingesting a value of 0).

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Biography

Agus Sutomo is a Master of Industrial Engineering Student at Universitas Mercu Buana, Jakarta, Indonesia. Besides, he worked in power plants within the Department of Warehouse Management, mainly in the supply of spare parts. The focus of the research is on optimizing the process of procurement of spare parts in the fast-moving class.

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