INDONESIAN JOURNAL OF MULTIDISCIPLINARY SCIENCE

P-ISSN: 2808-5957
E-ISSN: 2808-6724

Forecast sales volume of aviation fuel in Jakarta using ARIMA Method to support inventory control

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Keywords:

ARIMA forecasting
safety inventory
management inventory

ABSTRACT

The civil aviation industry in Indonesia experienced a significant increase from 2009-2018. The increase occurred in passenger and cargo activities. However, the situation changed drastically when the Covid-19 pandemic occurred throughout the world in 2019. PT XYZ as a company need to adapt and optimize the business process. Inventory management is something that can be optimized. The aim of this research was to forecast aviation fuel demand in Jakarta and utilize the forecast result as a basis for inventory management. This research utilizes time series data on aviation fuel sales to determine demand estimates for the following month. The method used to forecast is the Autoregressive Integrated Moving Average. Furthermore, the forecast data is combined with information on storage capacity and historical data on product supply arrivals as input data in calculating safety stock to obtain more economical inventory management. The result of this research is that the best forecast avtur demand in Jakarta is using ARIMA (1,1,1). Safety inventory calculation based on demand forecasting with 90% cycle service level for Jakarta is 42,495 kiloLiter and PT XYZ still can reduce products in their storage worth IDR. 341.8 M in Jakarta to maintain the same cycle service level.

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INTRODUCTION

As a downstream oil and gas industry, aviation fuel is one of PT xyz's main business lines. In the period of 2014-2018, there has been an increase in passanger and cargo activity from 13,694,482 passenger and 1,324,745 Tonage cargo in 2014 to 18,247,272 passengers and 1,828,509 Tonage cargo in 2018 (BPS, 2019; Direktorat Statistik Distribusi, 2019). That condition contributed in aviation fuel sales from 4,875 M kilo Liter in 2016, increase 8,31% per year until 2018. However, the situation changed drastically when the Covid-19 pandemic occurred throughout the world in 2019. In facing challenges in an increasingly tough business world due to covid-19 outbreak, companies need to adapt and do some optimization.

PT XYZ is a company which manages and carries out the chain of downstream business activities and operations in the form of trading and fuel handling. In supporting these trading activities, PT XYZ needs to carry out several supporting activities such as fleet management of fuel tank trucks to transport products to final consumers, management of tankers fleet that have been rented from other companies to transport products purchased from refineries in Indonesia, and inventory management and storage facilities which includes regulating the number of stored products, supply management which is also related to the use of the tanker fleet, monitoring and maintaining the quality of products that will be distributed to consumers, and maintaining storage facilities

From the company's main activity, inventory management is something that can be optimized. A method that can be proposed to solve this problem is the application of the lean supply chain concept. This concept requires companies to provide products according to demand (Garcia-Buendia et al., 2021; Reyes et al., 2023), so demand forecasting is one of the important points that must be carried out and all business decisions are based on customers' demand. Companies engaged in sales will generally have problems with storage (Pasaribu,

2021; Santoso, 2021). PT XYZ must change its business strategy from initially pushing products to consumers into providing products in accordance of consumer needs. Product inventory is one of the current assets owned by the company. However, the quantity must be strictly maintained so that there is no excessive stock or shortage. To maintain the number of products in storage sufficient to meet consumer demand, but not too much, the concept of cycle inventory and safety inventory is used. Cycle inventory is products in storage that are used to meet demand within the delivery time range. Safety inventory is inventory that is designated if demand exceeds estimates. This is needed to overcome uncertainty (Chopra & Meindl, 2013).

However, this problem occurred in the company at least in 2020. If we analyze the condition of aviation fuel stock at the Soekarno Hatta airports, it can be seen that the condition is up to 80% of the maximum volume of storage facilities used. With declining sales conditions due to the Covid pandemic, storage conditions reaching more than 80% are oversupply. The condition of full stock in storage facilities owned has unfavorable effects on the Company's finances such as the amount of storage cost. Excessive supply causing increased storage costs and maintenance of storage facilities.

Jakarta is the capital of Indonesia which supports the country's economy. In terms of aviation fuel sales, Soekarno-Hatta airport in Jakarta accounts for 50-60% of aviation fuel sales in Indonesia every month. Therefore, Jakarta is the most ideal storage location to become a pilot project in storage analysis. If this project to perform lean supply concept can be implemented well in Jakarta, it will immediately have a significant impact on PT XYZ's overall aviation fuel storage costs. There are additional costs that must be incurred for inventory holding costs, including manpower costs and product depreciation, as well as investment in storage facility costs (Singha et al., 2018).

Good aviation fuel demand forecasting is very necessary to start implementing the lean supply chain concept in a company and then determine the best supply and storage strategy. Dey et al. (2023) conducted a reasearch that aims to determine the need for ethanol in India which is used as a fuel for blending gasoline products. India has a program to use 20% bioethanol as gasoline fuel on the market starting in 2025 in stages until it can be fully implemented in 2030. The research found that ARIMA is the most accurate among all the model which developed using time series data of historical gasoline consumption from 1997 to 2021.

Wibowo et al.'s (2017) research entitled "Time Series Machine Learning: Implementing ARIMA and Hybrid ARIMA-ANN for Electricity Forecasting Model" aims to predict the electricity consumption of household customers from several power classes, namely 450 VA, 900 VA, 1300 VA, and 2200 VA. ARIMA is used to build linear models while ARIMA-ANN is used to build non-linear time series models. The selection criteria for the goodness of the model used are Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE). The most important points resulting from this research include that of the many models formed, complex models do not always produce better models for forecasting. ARIMA is still one of the best forecasting tools.

The research about Inventory Planning conducted by Kourentzes et al. (2020) was motivated by the stigma that inaccurate forecasting will increase a company's operational costs, including the potential for losing customers due to out of stock or additional costs due to excess stock, as well as not achieving customer service level targets. Researchers did not focus on evaluating the forecasting model, but directly evaluate inventory performance. The result was that accurate forecasting has no direct effect on inventory performance. Decisions in inventory management will be taken very often in one period and each of these decisions will greatly influence optimization. Every adjustment made in inventory and supply will have an impact on optimizing storage costs and service levels.

Goltsos et al. (2022) conduct a research that concerned with the interaction and integration between demand forecasting and inventory control. The majority of research on demand forecasting and inventory control are separate. The results of forecasting with the best method are only the end of a research disregarding any subsequent stages of computation that are needed to transform forecasts into replenishment decisions.

The purpose of this study is to find out the results of forecasting aviation fuel demand in Jakarta using the ARIMA method and then calculate how much safety stock need for aviation fuel demand in Soekarno-Hatta airport, Jakarta. With the calculation of safety and cycle inventory, how much excess product is stored can be known and then reduction can be obtained through this study as its contribution to the issue discussed.

METHOD

The research was conducted at aviation fuel storage PT XYZ located in Soekarno-Hatta Internasional Airport, Tangerang Regency. There are several data needed for the research. First, sales data collection from January 2019 to July 2023 to make a forecasting model and have standard deviation of daily sales. The forecasting model is created using time series data from the sales data collection. A time series is an observation based on a time sequence. The research data used is based on time sequences such as daily, weekly, monthly. The analytical model provides a simple forecasting method that is able to describe patterns and trends in time series data. By time series analysis, the forecasting accuracies depend on the characteristics of time series of

demand. If the transition curves show stability and periodicity, we will reach high forecasting accuracies, whereas we can't expect high accuracies if the curves contain highly irregular patterns.

The second data required are the number of products stored on each date from May to July 2023 at the storage location and also the maximum storage capacity data at the storage location. The third data is historical data on aviation fuel supply for that locations. Three information will get from the third data namely average of supply lead time, deviation standard of lead time, and cargo volume of the supply. All of data were obtained from the company's internal data.

Autoregressive Integrated Moving Average (ARIMA)

The Autoregressive Integrated Moving Average (ARIMA) model is a method developed by George Box and Gwilym Jenkins around 1976 (Makridakis et al., 1998). This model is used for periodic series analysis. The ARIMA Box–Jenkins principle consists of three iterative steps of model identification, parameter estimation, and diagnostic checking steps (Fattah et al., 2018). The ARIMA model is denoted as ARIMA (p,d,q) with:

p = Autoregressive degree/order
d = difference
q = moving average of degree/order

The Autoregressive process

The Autoregressive (AR) model assumes that today's events *(Yt)* are influenced by the previous day and so on. Literally, each observation consists of a random component (random shock, *e*) and a linear combination of the previous observations. $\emptyset_p$ in this equation is the selfregression coefficient. The autoregressive model can be defined by equation (1):

$$Y_t = \emptyset_1 Y_{t-1} + \cdots + \emptyset_p Y_{t-p} + e_t$$

The Integrated process

The Jenkins box ARIMA model requires that the data being modeled is stationary in variance and mean. However, purely stationary data is very rarely found in real conditions. Integrated processes are the archetype of nonstationary series. A differentiation of order 1 assumes that the difference between two successive values of Y is constant and can be defined by equation (2):

$$Y_t = Y_{t-1} + e_t$$

The Moving Average Process

The current value of a moving averaging process is a linear combination of the current disturbance with one or more previous perturbations. The moving average order indicates the number of previous periods embedded in the current value. To predict the Y_t value based on past linear combinations, or it can be formulated as follows equation (3):

$$Y_t = e_t - \theta_1 e_{t-1} - \cdots - \theta_q e_{t-q}$$

The Box–Jenkins principle consists of three iterative steps of model identification, parameter estimation, and diagnostic checking steps. Diagnostic checking is usus to determine whether the residual meets white noise and have normal distribution.

Inventory Management

Inventory is needed if there is an imbalance between delivery (supply) and demand (demand). For example, imbalances occur in businesses that will be more economical if they produce more than demand to anticipate future demand or face demand that often increases at certain times. Cycle inventory can follow equation (4):

$$cycle\ inventory = \frac{lot\ size}{2} = \frac{Q}{2}$$

Where *Q* is lot size of supply product. Cycle inventory is products in storage that are used to meet normal demand within the delivery time range. So in other words, the number of inventory cycles is demand during the lead time period. If D_i daily demand of the product and *L* is Lead time of product supply, the demand within lead time period (D_L) is define by equation (5):

$$D_L = \sum_{1}^{L} D_i$$

In the trading business, there is bound to be demand uncertainty. Apart from experiencing demand uncertainty, the Company will always be faced with supply lead time uncertainty (Gupta & Maranas, 2003). In many situations, supply uncertainty is a significant part. To be able to identify uncertainty in supply, it is

necessary to take into account the standard deviation to calculate total demand for the lead time duration as follows equation (6):

$$D_L = D\ x\ L\ ;\ \sigma_L = \sqrt{L\sigma_D^2 + D^2 s_L^2}$$

Where D is average demand per period, σ_L standard deviation of total demand over the lead time duration, σ_D is standard deviation of demand in certain period, S_L is standard deviation of lead time. And cycle inventory can follow equation (7):

$$ss = F_s^{-1}(CSL)\ x\ \sqrt{L\sigma_D^2 + D^2 s_L^2}$$

Where CSL is cycle service level or the possibility of how much inventory can meet consumer demand so that stockouts do not occur (Achkar et al., 2024; Cardós et al., 2009). The CSL value determined by PT xyz is 90%.

RESULTS AND DISCUSSION

Based on the Box–Jenkins approach, our forecasting will be carried out in three parts: identification, estimation, and verification. The model shown in Figure 1 is based on the demand of the product in Soekarno Hatta Internasional airport from January 2019 until July 2023.

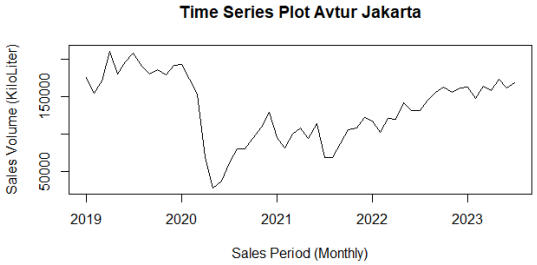


Figure 1. Time series plot of Avtur Sales in Jakarta

To test whether the data is stationary in terms of variance, a box-cox test is carried out to determine the lambda value of the data. Graph of box cox test results as in figure 2.

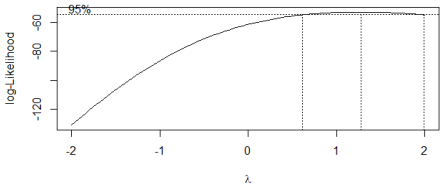


Figure 2. Box-Cox Testing graph

The lambda (λ) value is 1.27 and has a lower limit that passes the value 1 so it can be considered that the data is stationary in terms of variance. But the data is not statinary in average from Augmented Dickey Fuller (ADF) test. So in this case, need to do differentiation. (equation 2). The test hypothesis in ADF testing is:

H_0: The series has a unit root.

H_1: The series does not have a unit root. The series is stationary.

The results of the ADF test on data that has been differentiated once has an ADF Test value = -4.1856 with a p-value = 0.01, which means there is enough evidence to reject H0 so that the data is stationary in the mean with the d value in ARIMA (p, d,q) is 1. When the data is stationary, the p and q orders can be identified based on the ACF and PACF diagrams as in figure 3.

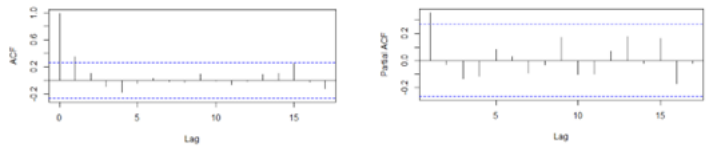


Figure 3. ACF and PACF

From the ACF diagram it can be seen that there is a lag that cuts off after the 1st lag so that q = 1, and the PACF can be seen as a cut off after the 1st lag so that p = 1 so that several models are obtained whose parameters are then estimated as follows:

Table 1. ARIMA Parameter Estimation

Model -	ARIMA Model	Parameter	Estimate
1	ARIMA (0,1,0)	-	-
2	ARIMA (1,1,0)	$\widehat{\emptyset}_1$	0,1112
3	ARIMA (1,1,1,)	$\widehat{\emptyset}_1$	-0,4125
		$\hat{\theta}_1$	0,5310
4	ARIMA (0,1,1)	$\hat{\theta}_1$	0,1256

From several models that have been identified above, a model evaluation is then carried out to determine the best model as in table 2:

Table 2. ARIMA Parameter Estimation

Alternative Orde		ARIMA (0,1,0)	ARIMA (1,1,0)	ARIMA (1,1,1)	ARIMA (0,1,1)
Criteria	**AIC**	1228,87	1230,20	1231,97	1230,11
	MAPE	16,06	15,85	15,66	15,77
	RMSE	20574,83	20444,96	20398,48	20427,81
	MAE	15417,28	15591,87	15536,01	15591,78
	MPE	-3,06	-2,39	-2,55	-2,37
Diagnostic Residual	Ljung Box Test	0,8844	0,8631	0,8449	0,8667
	Kolmogorov-Smirnov Test	0,06	0,06	0,06	0,07

All models fulfill white noise so it is necessary to compare forecasting results based on AIC, MAPE, RMSE, MAE, and MPE with the training data used. The result is that ARIMA (1,1,1) is the best model in terms of MAPE and RMSE, while ARIMA (0,1,0) is the best based on AIC and MAE. From the two models, ARIMA (1,1,1) also has a better MPE so it is determined that forecasting for Jakarta uses ARIMA (1,1,1).

Forecasting results with ARIMA (1,1,1) for Jakarta's Soekarno-Hatta airport for the next 3 period are as follows:

Table 3. ARIMA Forecasting

Prediction Periode	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Agu-23	170.858	143.973	197.743	129.740	211.975
Sep-23	169.854	129.516	210.192	108.162	231.546
Okt-23	170.268	120.729	219.808	94.504	246.032

With fitted vs observation curve and forecasting plot as follow figure 4 and figure 5.

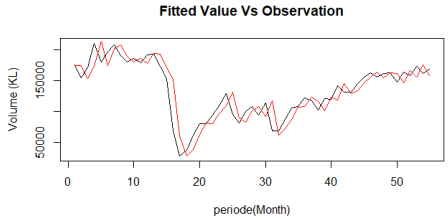


Figure 4. Fitted value vs Observation Plot

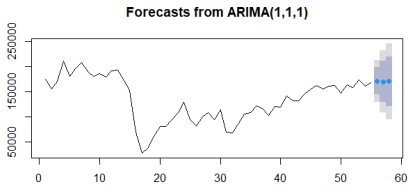


Figure 5. Forecasting plot

Cycle inventory can be approached by taking product needs during the Lead Time period of supply delivery. To be able to determine the inventory cycle, forecasted sales figures and the average lead time for product supply to that location are needed. Average lead time information is obtained from product supply arrival data to these locations over the last 3 months. Based on forecasting results, demand in August is 170,858 kilo Liter and lead time supply based on historical data for May-July 2023 is 4.38 days with a standard deviation of 2.16. From equation (5) and equation (6), cycle inventory for Jakarta airport will be 12,073 kilo Liter (Estimated demand *x* Lead time of supply). Added information that is also obtained from sales data is the standard deviation of demand in the last few months with value 310,66 kiloLiter so from equation (7) safety inventory (ss) is:

$$ss = F_s^{-1}(CSL)\ x\ \sqrt{L\sigma_D^2 + D^2 s_L^2} = NORMSINV(0{,}9)\ x\ \sqrt{4{,}38.\,310{,}66^2 + 170{,}858/30^2.\,2{,}16^2}$$
$$= 33.661\ kL$$

Analysis of stored product availability is carried out by analyzing the actual number of products stored compared to the optimal number (cycle plus safety inventory). The optimal number of products stored in a storage facility is safety inventory to deal with uncertainty and cycle inventory that is expected to meet demand. The results of the optimum stock calculation at DPPU can be presented in the figure 6.

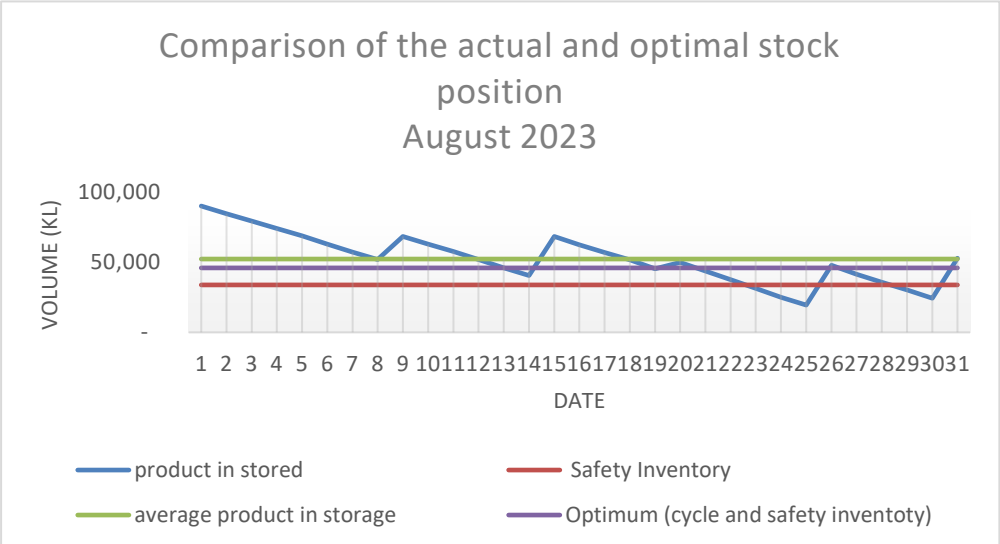


Figure 6. Actual Stock vs Optimum stock

Based on the graph above, it can be seen that the products stored in storage facilities exceed their optimum value. Based on product prices in August 2023 worth IDR 12,844/liter, PT xyz experiencing excess supply of IDR 81,2 Billion in August. This conditions cause an increase in storage costs (inventory holding

costs) and a trend in the need for investment in storage facilities (storage costs). For the Jakarta area, which is the center of government and economy in Indonesia, this is very good for the company's reputation. However, of course there are additional costs that must be incurred for inventory holding costs, including manpower costs and product depreciation, as well as investment in storage facility costs. (Singha et al, 2017).

CONCLUSION

The best results of forecasting aviation fuel demand using the ARIMA method for the four locations are Jakarta using ARIMA (1,1,1) based on a MAPE value of 15.66% and RMSE 20,398.48. In the period from August 2023, the safety inventory for Jakarta is 33,661 kL. There is potential for savings on aviation fuel purchases in August to reach 90% cycle service level in Jakarta amounting to IDR 81,2 B. Inventory management in a company requires detailed calculations regarding the costs incurred not only the price of the product. Conduct a study of the costs arising from inventory management activities starting from ordering costs, storage holding costs, storage costs, costs for deviation from the destination of the ship carrying the product to prevent stockout of product.

ACKNOWLEDGEMENT

This study was supported by Master Theses research grant 2024.

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