Forecasting export demand for L-Lysine as animal feed product in PT X Indonesia

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Abstract. PT X Indonesia is one of the foreign companies from South Korea that engaged in producing additional ingredients for animal feed. Located in Pasuruan - East Java, PT X is one of the industries producing L-Lysine and L-Tryptophan essential amino acids. L-Lysine and L-Tryptophan products are stimulants for animal feed which are exported to several countries. The planning of the production process is based on requests from the headquarters of PT X Indonesia in South Jakarta, Indonesia. To meet the needs of export products to several countries, PT X requires careful planning in providing the products. One of the determining factors in planning and providing products accurately, effectively, and efficiently is demand forecasting. This study aimed to forecast the export demand of L-Lysine. Historical data used for forecasting was time-series data from September 2019 to January 2020. The best ARIMA model combination chosen for forecasting was (1,0,1) because both the p-values for the AR and MA models are significant and it has the smallest Mean Square Error (MSE). Forecasting results use the ARIMA model showed that L-Lysine export for four weeks was in a range of 2,596.47 tons to 2,597.5 tons with a total of 10,387.9 tons and an average of 2,596.975 tons per week.

1. Introduction

PT. X Indonesia, located in Pasuruan - East Java, is one of the companies producing L-Lysine and L-Tryptophan essential amino acids. L-Lysine and L-Tryptophan products are stimulants for animal feed which are exported to several countries. To meet the needs of export products to several countries, PT X requires careful planning in providing the products. One of the determining factors in planning and providing products accurately, effectively, and efficiently is demand forecasting.

Demand forecasting can help PT. X Indonesia to predict market opportunities that are available in the future. Demand forecasting is used by companies in predicting the number of product demand in the next period. The purpose of a prediction is not to predict the conditions that occur in the future precisely, but to look for information that will be used as a reference for production. Planning processes in operations - e.g., capacity, production, inventory, and materials requirement plans - rely on a demand forecast. The quality of these plans depends on the accuracy of this forecast [1].

The performance of candidate models is evaluated either on in-sample data, usually using appropriate information, or by withholding a set of data points to create a validation sample (out-of-sample evaluation, also known as cross-validated error) [2]. Demand forecasting has several stages that need to
be considered so that the forecasting process is effective and efficient. Stages of demand forecasting begin with determining the objectives to be achieved from the implementation of forecasting, then selecting the predicted object [3]. The next step is determining the time horizon of the data is retrieved. The time horizon determines the forecasting method used to get the best results. The collected data is then needed to be predicted. After the data is collected, the appropriate forecasting model is selected and forecasting is finalized. Forecasting results are then analyzed and applied in the company.

2. Materials and Methods
Forecasting conducted in this study is quantitative forecasting using historical data regarding the number of export demand for L-Lysine products every week. The forecasting method used was the ARIMA method because ARIMA models are applied in some cases where data show evidence of non-stationarity, where an initial differencing step (corresponding to the "integrated" part of the model) can be applied one or more times to eliminate the non-stationarity [4]. In mathematics and statistics, a stationary process (or a strictly stationary process or strongly stationary process) is a stochastic process whose unconditional joint probability distribution does not change when shifted in time and consequently, parameters such as mean and variance also do not change over time [5]. Therefore, historical data will first be performed on the data stationarity test.

The historical data used was the export sales of L-Lysine 99% (L-Lysine HCL) products from the first week of September 2019 to the third week of January 2020. Forecasting was conducted from the fourth week of January 2020 to the second week of February 2020. The forecasting period is included in the medium-term forecasting category because the period of data used was more than three months [6].

3. Results and Discussion
Data on the number of L-Lysine 99% export sales (L-Lysine HCL) at PT X Indonesia, Pasuruan have a horizontal data pattern because the data does not increase or decrease during a certain time. Horizontal data patterns occur if the data fluctuates around a constant average value. A product whose sales have not increased or decreased during a certain time is included in the type of horizontal pattern [7]. For example, the sale of products that tend to be constant like groceries. Values of the average fluctuate around 2,495 tons per week and do not indicate repetitive data movements from one period to the next. The time-series graph from historical data on the number of export sales of L-Lysine 99% (L-Lysine HCL) products can be seen in Figure 1. Furthermore, it will be seen whether each data has been stationary towards the average and variance.

![Figure 1. A time series plot of export demand for L-Lysine.](image)

3.1 Stationary test of variance
Stationary tests of variance were carried out using Box-Cox plots from the export of 99% L-Lysine (L-
Lysine HCL). If the rounded value or lambda (λ) is equal to one, then the data is said to have been stationary for variance [8]. Box-cox plots from 99% L-Lysine exports can be seen in Figure 2. The Box-Cox plot showed a rounded value of one. It means that the data was in a stationary state of the variety and does not need to be transformed.

Based on Figure 2, we can see the Lower Control Limit and Upper Control Limit of lambda, in which these values were confidence intervals for the Box-Cox transformation. Those can be asymptotically constructed using Wilks's theorem on the profile likelihood function to find all the possible values of λ and showed in the graph by using vertical lines. The rounded value of lambda was more considered to be used for data transformation than the estimated value because the rounded value was said to the optimum value of lambda [9].

3.2 Stationary test of average

The stationary test of average was analyzed using the autocorrelation function graph. The autocorrelation function (ACF) graph displayed the autocorrelation function and lag. At lag k, the bar height represents the autocorrelation coefficients between series values that are k intervals apart [10]. If the first three lags in the autocorrelation function plot have crossed the red line (significance limit), it means that there is still autocorrelation and the data is not stationary in the average, so that it needs differencing [11]. The plot of the L-Lysine 99% export autocorrelation function (ACF) can be seen in Figure 3.

![Box-Cox plot of L-Lysine exports](image1.png)

**Figure 2.** Box-Cox plot export demand of L-Lysine.

![ACF plot of L-Lysine exports](image2.png)

**Figure 3.** ACF plot of export demand of L-Lysine.
In Figure 3, no lag comes out of the red line, which is the red line is a confidence interval [12]. This shows that the historical data on the number of L-Lysine export sales of 99% (L-Lysine HCL) has been stationary to average. Moreover, the data was tested using the partial autocorrelation function (PACF) plot as further testing to ensure that the data was stationary on average.

The PACF plot showed stationary patterns because no lag value exceeds the red line. These results were similar to the previous autocorrelation function or ACF plot. This concludes that the data on the amount of L-Lysine 99% export sales (L-Lysine HCL) was stationary to average. The results of the partial autocorrelation function graph of the total L-Lysine export sales of 99% can be seen in Figure 4.

3.3 Forecasting of export demand of L-Lysine

ARIMA model or Auto-Regressive Integrated Moving Average is a technique to find the most suitable pattern of a group of data, by utilizing the past and present data of the dependent variable to make accurate short-term forecasting [13]. The ARIMA model can predict irregular data due to data fluctuations [14]. The determination of the ARIMA model is determined by three general components namely \((p, d, q)\), where \(p\) has the meaning of the autoregressive order, \(d\) means the level of differentiation (differencing) and \(q\) is the order of the moving average [15]. The best model was said to have a \(p\)-value less than 0.05 (\(p < 0.05\)) which means that it was significant and it has the smallest mean square error (MSE) value than the other models. The results of the significance test on a combination of the ARIMA model can be seen in Table 1.

| Model  | Type | \(P\)-Value | RMSE  |
|--------|------|-------------|-------|
| (1,0,0) | MA 1 | 0.000       | 803.807 |
| (1,0,1) | AR 1 | 0.000       | 649.819 |
|        | MA 1 | 0.000       |       |
| (0,0,1) | AR 1 | 0.000       | 1,606.82 |

The best ARIMA model of the three models was ARIMA (1,0,1) with both AR and MA \(p\)-value of zero so that it indicates the AR and MA models are significant, and it has the smallest RMSE value of 649.819. The square root of the sum of the square of the deviation of the predicted values from the observed value dividing by their number of observation is known as the root mean square error [16]. Hence, demand forecasting using the ARIMA (1,0,1) model was done to find out the next period for the next 4 weeks. The results of forecasting can be seen in Table 2.

Forecasting results using the ARIMA model with a range of 2,596.47 tons to 2,597.5 tons in one week with a total of 10,387.9 tons and an average of 2,596.975 tons per week. To compare, the actual data of L-Lysine exports 99% can be seen in Table 3. The actual data of L-Lysine exports obtained from
companies tend to fluctuate with an average weekly sales of 2,563.75 tons and total sales of 10,255 tons for 4 weeks. From these results, it can be seen the difference between the results of forecasting and actual data was 33,225 tons on average. Forecasting results can be used by companies because it is not much different when compared with the average value of the actual data. Therefore, the forecasting model can be said to be sufficiently accurate to be used in forecasting L-Lysine export sales. However, the results of forecasting tend to be constant whereas the actual data obtained tend to be volatile. Forecasting results tend to be a constant possibility of a lack of data that represents for forecasting. The more data used, the more accurate the data will be [17]. Actual data has fluctuations that cause irregular data movements, caused by events that occur such as sudden export demand rises and competition so that product demand also decreases. Animal feed sales tend to fluctuate depending on consumer demand and the number of competitors of similar products [18].

Table 2. Forecasting of export demand of L-Lysine.

| Period 2020 | Week | Forecasting Results (ton) |
|------------|------|---------------------------|
| January    | 4    | 2,597.49                  |
|            | 5    | 2,597.15                  |
| February   | 1    | 2,596.81                  |
|            | 1    | 2,596.47                  |
| Total      |      | 10,387.9                  |
| Average    |      | 2,596.975                 |

Table 3. Actual export demand of L-Lysine 99% from January 2020 to February 2020.

| Month | Week | Real export demand (ton) |
|-------|------|--------------------------|
| January | 4  | 1,847                    |
|        | 5  | 2,076                    |
| February | 1  | 2,997                    |
|        | 2  | 3,308                    |
| Total  |      | 10,255                   |
| Average       |      | 2,563.75                 |

Forecasting results can be used by companies because it is not much different when it was compared to the average of actual data, so the forecasting model can be said to be accurate enough to be used in forecasting L-Lysine export sales. Based on Singh et al [19], to find the best prediction model can be done by looking at the error level generated, where if a smaller error value is the best model. Therefore, may in another case, the reason why the forecasting result is significantly different from the actual condition is because of the error value. Forecasting serves to make decisions in the company and measure or estimate the situation in the future [20]. Forecasting results can be used as a benchmark to calculate the amount of inventory in the coming period. So far, the company has only relied on the number of requests from the central company. This can lead to an error in the form of a delay in the arrival of raw materials caused by inaccurate time for the next period so that the production process can be hampered.

4. Conclusions
The forecasting result of export demand of L-Lysine with a total of 10,387.9 tons and an average of 2,596,975 tons per week. The company can use these results to make a plan related to the needs of raw materials, labor, machinery, and others. Product demand forecasting is very useful especially for products that are made by order because the number of needs related to the production process can be adjusted to the number of demands. Ordering of raw materials, the number of workers, setting working hours, engine maintenance, and others can be well prepared if the company knows the predicted market
demand for its products. If properly prepared, constraints such as lack of raw materials, the amount of production that exceeds production capacity, or damage to the machine will be controlled. Thus, consumers will feel satisfied not only with product quality but also with the services provided by the company.

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