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Forecasting Analysis of Indonesia's Shrimp Export to Japan

Rhochmad Wahyu Illahi[1*], Shwu-En Chen[2], Ratya Anindita[3]

[1]Student of International Agribusiness Management, National Pingtung University of Science and Technology, Shuefu road, Pingtung 91201, Taiwan
[2]Professor of Agribusiness Management Faculty of National Pingtung University of Science and Technology, Shuefu road, Pingtung 91201, Taiwan
[3]Professor of Economic Agriculture Faculty of Brawijaya University, Veteran road, Malang 65145, Indonesia

***Corresponding author:** Rhochmad Wahyu Illahi
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Abstract **Original Research Article**

Forecasting is attempted to predict future circumstances and events through testing the situation in the past. The purpose of this study was to analyze the best model to forecast Indonesia's shrimp export to Japan. Data of Indonesia's Shrimp exports are time series during 1989-2017. Moving Averages, Single Exponential Smoothing, Least Squares Trend, Quadratic Trend, and Box-Jenkins (ARIMA) models were used to predict the Indonesia's shrimp export to Japan during 1989-2017 and to forecast export in 2018. Then, the forecast error analysis was analyzed by MAPE (Mean Absolute Percentage Error), MAD (Mean Absolute Deviation), and MSE (Mean Square Error. Minitab 17 application and Microsoft Excel were used for data analysis. As a result, ARIMA was selected as the best model as forecasting model because it has the smallest forecasting errors evaluated by MAPE, MAD, and MSE and is able to predict more accurately than other forecasting models.
Keywords: Shrimp Export, Forecast, Indonesia, Time Series, ARIMA.

Introduction

Indonesia, the largest shrimp producer in the world, exports shrimp mainly to the US and Japan, accounting for more than one third of the shrimp export. The shrimp catch results and exports fluctuate in different seasons and different years. It is important to adopt an accuracy method to forecast export as a guideline for management strategy and agricultural policy [1].

The major export commodities of Indonesian fishery products are shrimp, tuna, grouper, snapper, mackerel, tilapia, cephalopoda (squid, octopus, and cuttlefish), crabmeat, crab, seaweed, sea cucumber, and lobster. Export of the products can be predicted by forecasting analysis. Then this study was to analyze the best model to forecast Indonesia's shrimp export to Japan [2].

Forecasting is the art and science of predicting future events. Forecasting basically requires the retrieval of historical data for projecting it to the future with mathematical modeling. It could be subjective or intuitive prediction of the future. Forecasting can include combination of mathematics models to good judgment by managers [3]. Forecasting is a process to estimate some future about quantity size, quality, time and location required in order to demand for goods or services [4].

In general, the purpose of this study is to forecast of Indonesia's shrimp export to the main destination country, Japan. Specifically, the objectives of this study are: (1) to forecast Indonesian shrimp export to Japan, and (2) to find the best model to forecast Indonesia's shrimp export to Japan after comparing different models.

Order forecasting is directly linked to production planning and control while prediction is the more general statement. The prediction is calculated on the basis a model, and the model is usually obtained by a fit to some available data. The predictor may be continuous like continuous "time". In this case the model gives you an expected value for any possible value of this predictor. Here it is possible to predict value at time points for which no data exists. When such a prediction is done for times within the range of observed time points it is called an interpolation. When the prediction is done outside of the range of observed time points it is called an extrapolation. So far this all applies to any kind of continuous predictor (like concentration, mass, distance, speed, and so forth). The "time" is somewhat special because it has a natural "direction", from past to future, and time-series analyses usually perform to make predictions of future observations and this is called a forecast [5].

METHODOLOGY

Time series methods are used for forecasting and there's used historical data about export. The method of export product forecasting used in this study is the method of quantitative forecasting. The method is time series consisting of Moving Averages model, Single Exponential Smoothing model, Least Square Trend model, Quadratic Trend model, and Box-Jenkins model (ARIMA). In essence the prediction is only an approximation, but by using a certain technique, then the prediction becomes more than an approximation [6].

Moving Average Model (MA Model)

Moving Average is used to illustrate this approach. Each new observation becomes available, a new average calculated by summing up the most recent value and removing the oldest. Moving average is more used to predict the next period [7].

Equation (1) is the moving average formula to forecast:

$$S_t = (X_t+X_{t-1}+X_{t-2}+\ldots+X_{t-n})/n \qquad (1)$$

Where:
S_t = export prediction at period t
t = period of time (year)
n = number of period
$X_t, X_{t-1}, X_{t-2}, X_{t-n}$ = actual export at period t, t_{-1}, t_{-2}, t_{-n}

Single Exponential Smoothing Model

Exponential smoothing model was called an "exponentially weighted moving average", which is easy to be understood and to explain what does exponential smoothing means [7]. Technique was developed around 1950's and there were a many different possibilities to do with exponential smoothing. Forecasting using the exponential smoothing model is performed based on the equation (2):

$$S_t = S_{t-1} + \alpha\,(X_{t-1} - S_{t-1}) \qquad (2)$$

Where:
S_t = export prediction at period t
S_{t-1} = export prediction at period t-1
α = Smoothing coefficient ($0 < \alpha < 1$)
X_{t-1} = actual export at period t-1
t = period of time (year)

Least Square Trend Model (Linear Trend)

Least squares trend analysis model as a tool to estimate using the data owned to determine the linear relationship. Equation (3), (4) and (5) are the formula to forecast [8]:

$$Y = a + bX \qquad (3)$$

$$a = \ddot{Y} - b\ddot{X} \qquad (4)$$

$$b = \frac{\Sigma XY - n\ddot{X}\ddot{Y}}{\Sigma X^2 - n\ddot{X}^2} \qquad (5)$$

Where:
a = intersection of axis Y
b = slope of the regression line
Y= dependent variable
X= independent variable
$\ddot{X}$= average value X
$\ddot{Y}$= average value Y
n = number of observations

Quadratic Trend Model (Non-Linear Trend)

Quadratic trend analysis model is a trend analysis that is non-linear or possibly not linear in the short term. Equation (6), (7), (8) and (9) are the formula to forecast [8]:

$$Y = a + bX + cX^2 \qquad (6)$$

$$a = \frac{(\Sigma Y)(\Sigma X^4) - (\Sigma X^2 Y)(\Sigma X^2)}{n(\Sigma X^4)(\Sigma X^2)^2} \tag{7}$$

$$b = \frac{\Sigma XY}{\Sigma X^2} \tag{8}$$

$$c = \frac{n(\Sigma X^2 Y) - (\Sigma X^2)(\Sigma Y)}{n(\Sigma X^4)(\Sigma X^2)^2} \tag{9}$$

Where:
a = axis intersection
b = slope of the regression line
c = slope of the regression line for X^2
X = 0 at the middle of the odd period series
= -1, -2, before the middle period in the time series
= 1, 2, after the middle period in the time series
Y = time series data
n = number of observations

Box-Jenkins Model (ARIMA Model)

Box-Jenkins Model (ARIMA) is called approaching model [9]. Box-Jenkins models are grouped into three: (1) Autoregressive (AR) Model, (2) Moving Average (MA) Model, (3) Mixed Model. This mixed model can be a mixed model of the Autoregressive Moving Average (ARMA) model and the Autoregressive Integrated Moving Average model. If the stationary series is a linear function of sequential past values, the equation is called the autoregressive model. The equation of this model is [10]:

$$Y_t = b_0 + b_1 Y_{t-1} + b_2 Y_{t-2} + ... + b_n Y_{t-n} + e_t \tag{10}$$

If the stationary series is a linear function of current and past forecasting errors, it is called the moving average model. The equation of this model is [10]:

$$Y_t = a_0 - a_1 e_{t-1} - a_2 e_{t-2} - ....- a_n e_{t-n} + e_t \tag{11}$$

Time series (stationary random) cannot be explained only by the moving average model or autoregressive, because the process contains both. Therefore, the combination of the two models, called the Autoregressive Integrated Moving Average (ARIMA) model. In this model combined the stationary series is a function of its past value and present value and past errors. The equation of this model is [10]:

$$Y_t = b_0 + b_1 Y_{t-1} + ... + b_n Y_{t-n} - a_1 e_{t-1} - ... - a_n e_{t-n} + e_t \tag{12}$$

Requirements are needed so that the process is stationary is $b_1+b_2+...+b_n <1$.

This process is represented by ARIMA (p, d, q). Where: p indicates the order / degree of autoregressive (AR) d is the level of differencing process and q shows the order / degree of moving average (MA). To determine the ARIMA model (p, d, q) which is suitable (tentative), meaning to specify how many p, d, and q. If without differencing process d is given a value of 0, if it becomes stationary after first order differencing d is worth 1 and so on. In choosing how many p and q can be helped by observing the patterns of autocorrelation and partial autocorrelation functions. If the autocorrelation exponentially weakens to zero means an AR process. If the partial autocorrelation weakens exponentially, its mean the MA process. If both are weakened, its mean ARIMA processes [11].

Accuracy

The size of forecasting accuracy is done by measuring forecasting errors which are the degree of difference between forecasting results and actual export. The measurement of error used in this research is mean absolute percentage error (MAPE), mean absolute deviation (MAD), and mean square error (MSE) [4].

Mean Absolute Percentage Error (MAPE)

MAPE is a relative error measure that states the percentage of error forecasting results against actual requests over a given period that will give the error percentage information too high or too low [4]. MAPE is formulated as follows:

$$MAPE = \frac{\Sigma |At-Ft| /At}{n} \times 100\% \quad (13)$$

Where:
At = Actual value at period t
Ft = Forecasting value at period t
n = Number of forecasting periods

Mean Absolute Deviation (MAD)

MAD is the average of absolute error over a given period regardless of whether the forecasting result is greater or less than the actual value or reality. Mathematically MAD is formulated as follows [4]:

$$MAD = \frac{\Sigma |At-Ft|}{n} \quad (14)$$

Where:
At = Actual value at period t
Ft = Forecasting value at period t
n = Number of forecasting periods

Mean Square Error (MSE)

Mean of error quadratic or MSE is calculated by summing the squares of all forecasting errors in each period and dividing by the number of forecasting periods. Mathematically MSE is formulated as follows [4]:

$$MSE = \frac{\Sigma [At-Ft]^2}{n} \quad (15)$$

Where:
At = Actual value at period t
Ft = Forecasting value at period t
n = Number of forecasting periods

Comparison Criteria of the Best Model Forecasting

The measurement of error used in this research is mean absolute percentage error (MAPE), mean absolute deviation (MAD), and mean square error (MSE). From these three measurements can be seen the error generated. The smallest error indicates that this model is better than the other model. Compared with MAD and MSE, MAPE is usually more meaningful because MAPE declares the percentage of error forecasting results against actual requests over a given period that will give the error percentage information too high or too low [4].

Results and Discussion

Forecasting with Moving Average Model (MA Model)

The Moving Average model is a forecasting model that uses data of Indonesia's Shrimp Export to Japan in past periods in sequence. The request data is smoothed out. The term moving average is raised because the average price is calculated continuously by removing the data for a long period and replacing them with new period data [11]. This model has a data length of at least 3 periods.

The results of Indonesia's Shrimp Export in 2018 are 27,080,419 Kg (moving average 3 period). The results of forecasting with moving average are illustrated through the following graph (Figure 5).

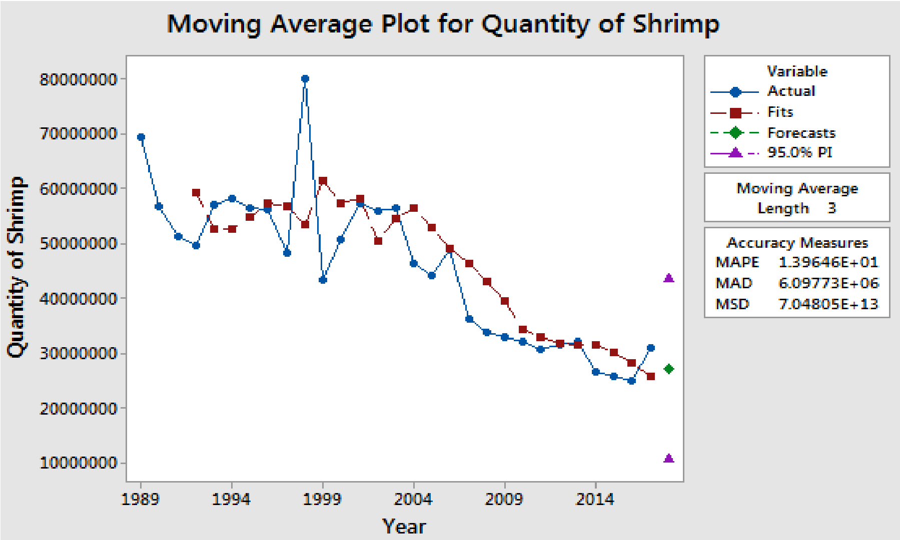

Fig-5: Graph of Forecasting Indonesia's Shrimp Export to Japan with Moving Average Model (3 period)

Forecasting with Single Exponential Smoothing Model

Forecasting with Single Exponential Smoothing model is a procedure that repeats calculations continuously using the latest data based on the calculation of the average forecasting of the latest observation objects [11]. Forecasting with the single exponential smoothing model in this study tried to use different smoothing coefficients. The smoothing constant is in the range $0 \leq \alpha \leq 1$. There are $\alpha = 0.2$; $\alpha = 0.5$; and $\alpha = 0.9$. The result from forecasting with single exponential smoothing constant that have smallest forecast error rate.

Single Exponential Smoothing Model with smoothing coefficient $\alpha = 0.2$; $\alpha = 0.5$ and $\alpha = 0.9$, respectively is 30,942,641 kg; 28,444,131 kg; and 30,191,341 kg. The graph of forecasting for Indonesia's Shrimp Export with smoothing constants α=0.2; α=0.5; and α=0.9 can be seen in the Figure 6, 7, and 8.

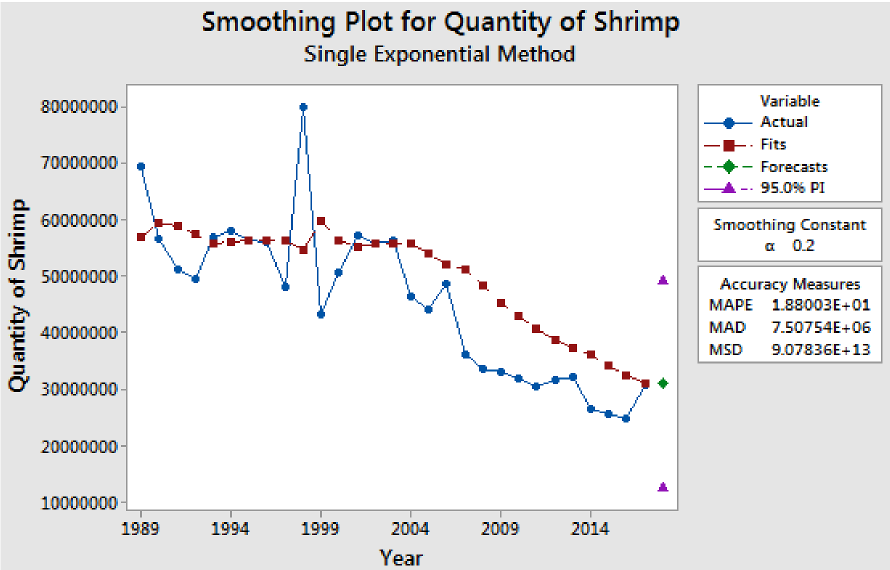

Fig-6: Graph of Forecasting Indonesia's Shrimp Export to Japan with Single Exponential Smoothing Model (α = 0.2)

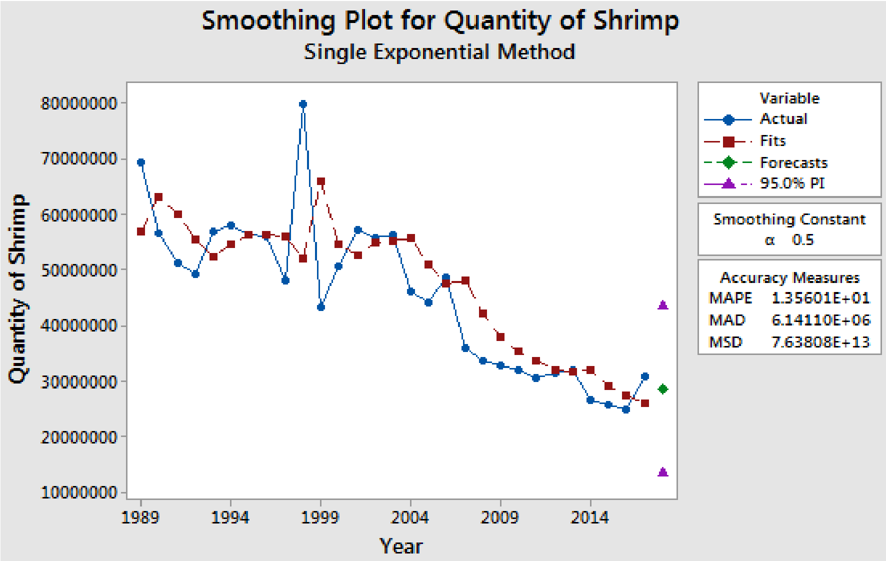

Fig-7: Graph of Forecasting Indonesia's Shrimp Export to Japan with Single Exponential Smoothing Model (α = 0.5)

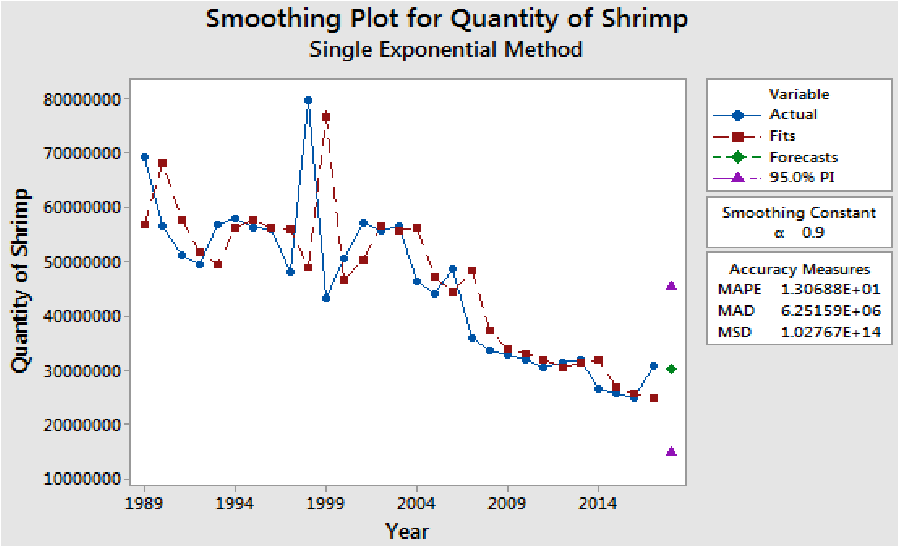

Fig-8: Graph of Forecasting Indonesia's Shrimp Export to Japan with Single Exponential Smoothing Model (α = 0.9)

Forecasting with Least Squared Trend (Linear Trend Model)

The least squares model or Linear Trend tries to adjust the line with data that minimize the sum of squares from the vertical distance between each data point and the point associated with that line. If the line of a straight line is drawn through the gathering area of these points, the difference between the point and the line is ŷ-y [12]. Results of forecasting for Indonesia's shrimp export with Least Square Trend model can be seen in the Figure 9.

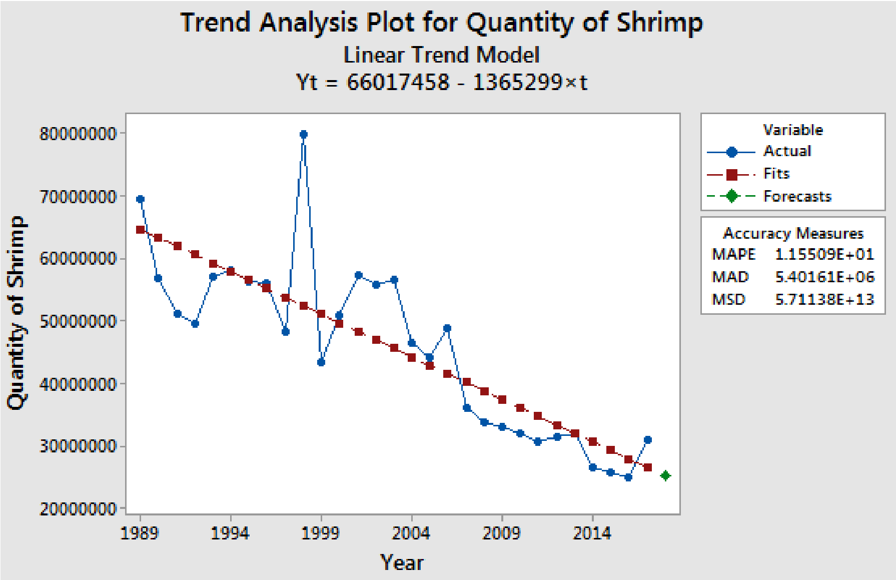

Fig-9: Graph of Forecasting Indonesia's Shrimp Export to Japan with Least Square Trend Model (Linear Trend Model)

The graph in Figure 9 is a graph of the results of forecasting Indonesia's shrimp export with the Least Square Trend that help Minitab version 17 program which has the equation Yt = 66017458 – 1365299xt. The blue line is the actual value; the red line is the forecasting for the period according to the data, while the green dot shows the forecasting for the next period in the 30th period.

Forecasting with Quadratic Trend (Non Linear Trend Model)

Quadratic Trend Analysis is a trend analysis that is non-linear or which is not likely to be linear in the short term [8]. Just like the Least Square Trend model, in this model the time series data is collected as Y. Then the data X is obtained from numbering odd data is divided into two and the middle data position starts with 0. The difference with the Least Square Trend model. In this model, searched the value of XY, X^2 and X^4. After that searched the coefficient value a, b and c for the equation $Y = a + bX + cX^2$. Results of forecasting for Indonesia's shrimp export with Quadratic Trend model (quadratic) can be seen in the Figure 10.

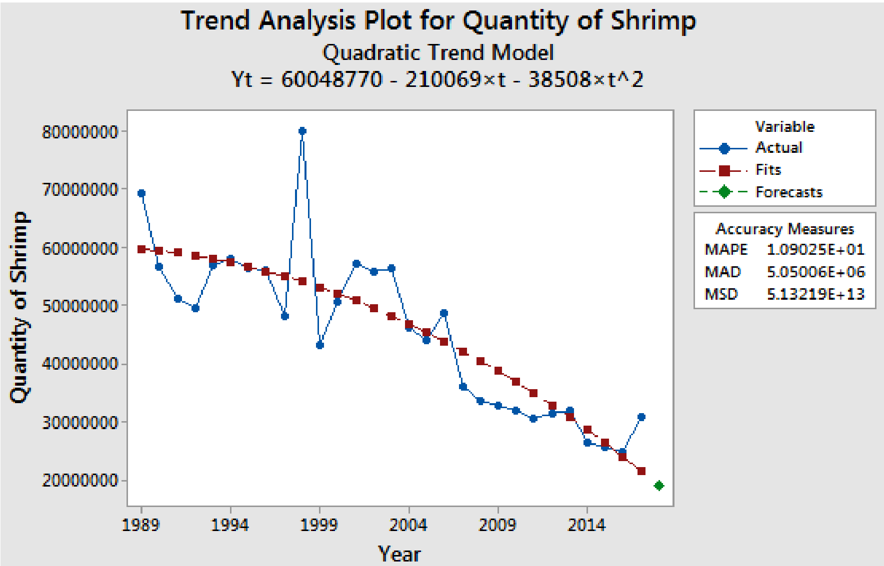

Fig-10: Graph of Forecasting Indonesia's Shrimp Export to Japan with Quadratic Trend Model (Non Linear Trend Model)

In Figure 10 is a graph of the forecasting results of Quadratic Trend model with the help of the Minitab v.17 program which has the equation Yt = 60048770 – 210069xt – 38508 xt^2. The blue line is the actual value, the red line is forecasting for the same period according to the data, while the green dot shows the forecasting for the next period, namely the 30th period.

Forecasting with Box-Jenkins Model (ARIMA Model)

The ARIMA model (Autoregressive Integrated Moving Average) or known as the Box-Jenkins model is a form of time series analysis used to analyze stationary data, so that data that is not stationary is transformed or differencing. The following stages of the forecasting process using the ARIMA model:

Time Series Data Plot Test

The first step in the ARIMA model forecasting process is to test the data by making time series data plots. Data plots were used to determine data patterns and series trends of time series data observations. From the results of the plot data can be seen whether a series value has a stationary, trend, or seasonal element [9]. The result of a time series data plot from the export for Shrimp products using the Minitab computer program v.17 can be seen in the Figure 11.

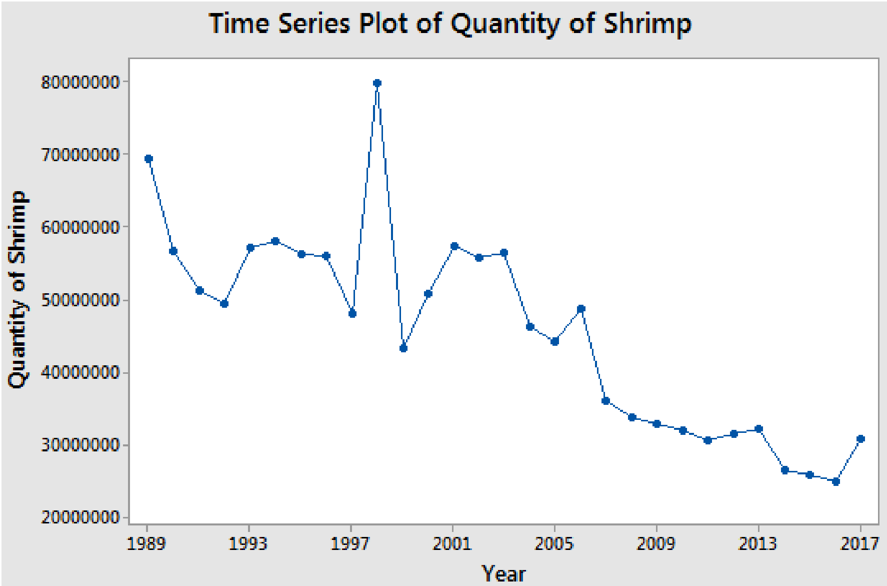

Fig-11: Graph Time Series of Plot Indonesia's Shrimp Export to Japan (1989-2017)

Based on the graph in Figure 11, it can be seen that the Indonesia's shrimp export data does not have trend elements, but shows irregular or fluctuating time series patterns. The data plot results cannot be fully valid in interpreting whether the data pattern is said to be stationary or not, but must be accompanied by data analysis using other parameters by looking at the ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) plots.

Stationary Test Data

ARIMA model must use time series data which is stationary in variance and stationary in mean. Reveal that to identify stationary data in variance, data is implemented by Box-Cox Plot. While the stationary data in the mean uses plots ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function). For easier testing of stationary data, the Minitab computer program was used to create Box-Cox plots and ACF and PACF plots [13].

Differencing process using Box-Cox

Time series data for Indonesia's Shrimp export are identified using a Box-Cox plot to determine whether the time series data is stationary in variance or not. The Box-Cox plot is created with the help of the Minitab version 17 computer programs. The output is shown through a graph in Figure 12.

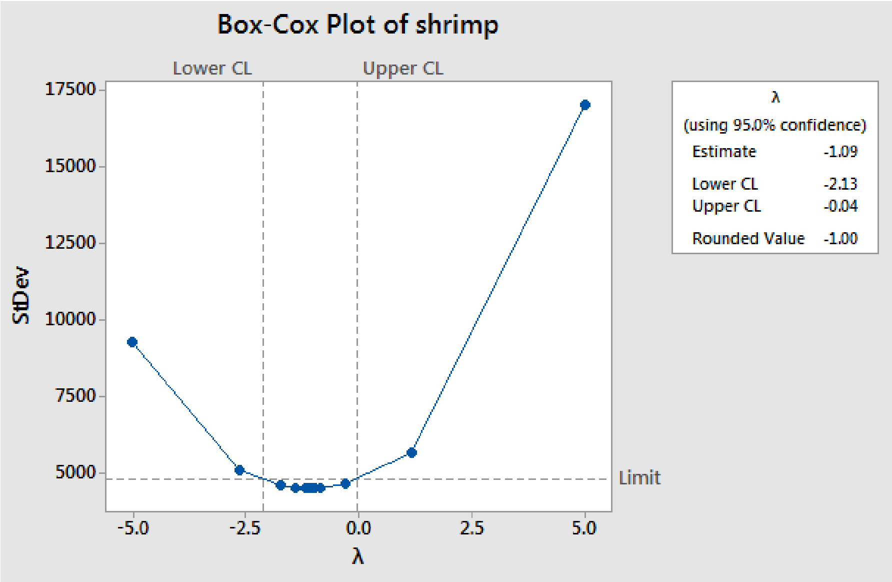

Fig-12: Plot Box-Cox Time Series of Indonesia's Shrimp Export

The output of the Box-cox plot from the Indonesia's Shrimp export data in Figure shows the Rounded Value of -1.00. This value still shows a negative number and is not worth 1.00. A time series data is said to be stationary in variance or variety if the value of Rounded Value shows a value of 1.00. Data that is not stationary needs to be transformed (difference) to the original data using Box-Cox transforms [13].

Rounded value is equal to -1.00 before transformation. So that the original data of the product request is to be transformed by using the Box-Cox transformation to achieve stationary variety. The results of the Box-Cox transformation of the original data can be seen in the Figure 13.

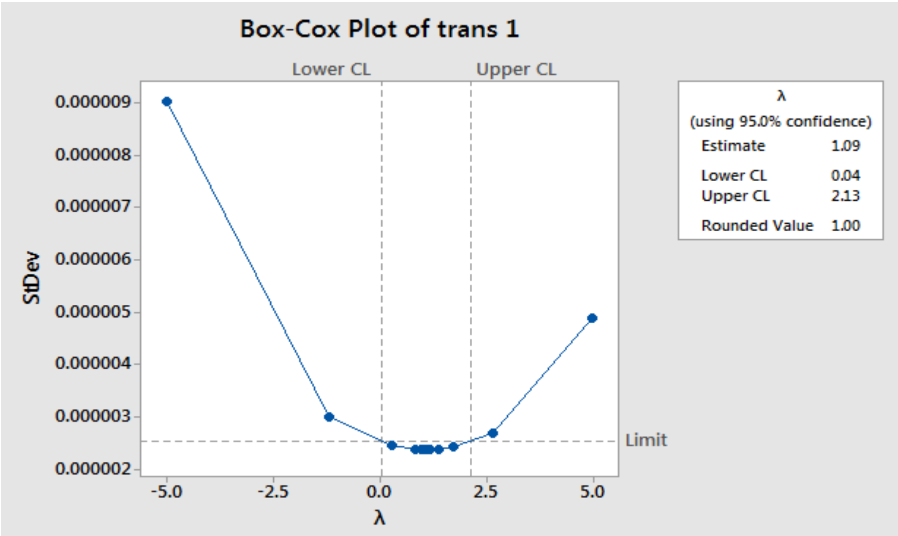

Fig-13: Plot Box-Cox Time Series of Indonesia's Shrimp export to Japan Transformasi Box-Cox

After the transformation, the results of the Rounded Value are still showing the number -1.00, so it needs to be transformed again with the results of the first transformation (difference 1) transformed by Box-Cox transformation. Then the transformation results are obtained with a Rounded Value of 1.00 so that the data is stationary in variety.

Autocorrelation Function (ACF)

After transformation, the time series data resulting from the transformation is calculated using ACF values and ACF (Autocorrelation Function) plots. The calculation of the ACF value and the making of the plot in this study were carried out with the help of the Minitab version 17. Indonesia's Shrimp export shows the amount of lag and also shows the ACF value, statistics and the Ljung-Box Q (LBQ) statistical value. From the results it can be seen that the time series data shows the amount of lag as much as 25.

Autocorrelation shows the relationship between the value of a variable and its past value, which is called a lag of one or more. The autocorrelation coefficient ranges between -1 and +1, where 0 indicates that there is no correlation. If the series is random or stationary, then the entire autocorrelation coefficient must be significantly different from zero or only a few lags in front differ in zero and then not different from zero [10]. Output of autocorrelation analysis results in the form of ACF plot graph, can be seen in the Figure 14.

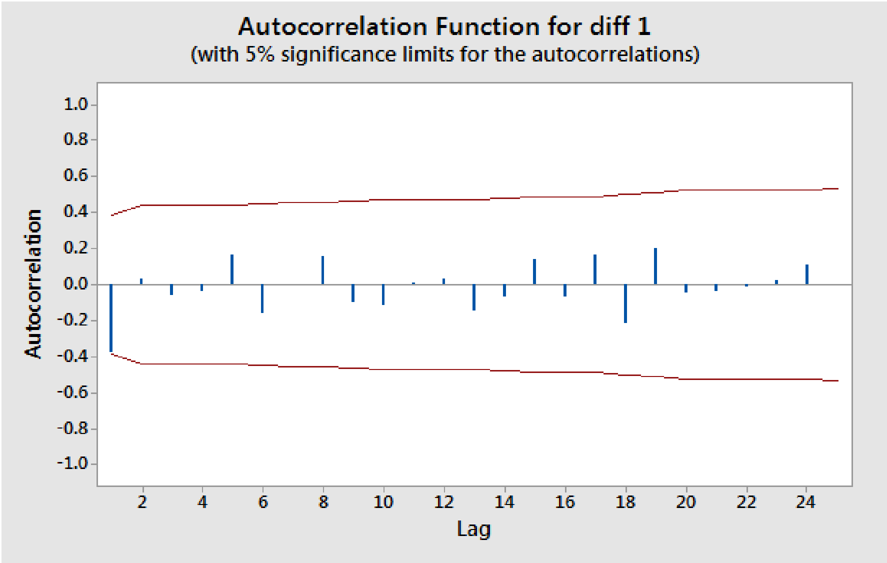

Fig-14: Graph of Autocorrelation Function (ACF)

In Figure, the red line on the chart is a confidence interval which is the boundary line of autocorrelation significance. If there are 3 or more first lags passing through the line then the data is not stationary. In the graph it can be seen that there is no lag whose value crosses the autocorrelation significance line so that it can be said that the data has been stationary. The ACF values on the chart form an ACF pattern that drops exponentially on positive and negative. Meanwhile, if stationary is only seen based on ACF values and plots, it is still not enough, it needs to be reviewed based on the PACF value and plot.

Partial Autocorrelation Function (PACF)

The analysis output of the partial autocorrelation function (PACF) is the same as the ACF output which is in the form of output in the Window Session and also in the form of a PACF plot graph [10]. Result of partial autocorrelation (PACF) can be seen in the Figure 15.

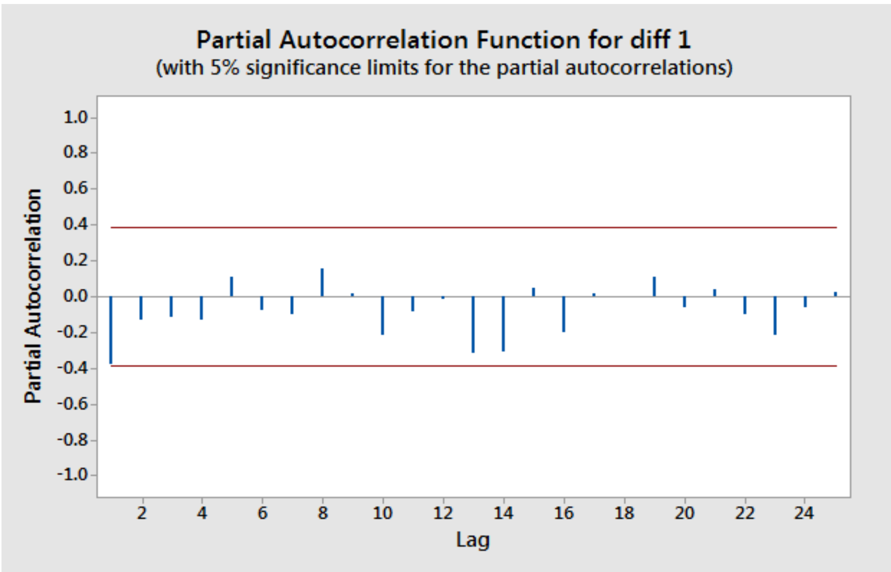

Fig-15: Graph of Partial Autocorrelation Function (PACF)

The PACF plot in Figure shows the red line on the graph is a confidence interval which is a partial line of significance of partial autocorrelation. If there are 3 or more first lags passing through the line then the data is not stationary. On the graph of the PACF plot it can be seen that there is no lag whose value crosses the red line so that it can be said that the data is stationary. PACF values on the chart form a PACF pattern.

ARIMA Model Estimation and Parameter Significance Test

ARIMA Model Estimation is step to detect some parameters or coefficients of the alternative ARIMA model (p, d, q) which is suitable (tentative), meaning to specify what p, d, and q are. If there is no differencing process, d is given a value of 0. If it becomes stationary after first order differencing, d is worth 1 and so on. Choosing the numbers of p and q can be helped by observing the patterns of autocorrelation and partial autocorrelation functions. In general, analysts must identify an autocorrelation that exponentially becomes zero. If the autocorrelation exponentially weakens to zero means an AR process. If the partial autocorrelation weakens exponentially, its mean the MA process. If both are weakened, its mean ARIMA processes.

ACF plot is used to determine the maximum order q in MA (q), while PACF plot is used to determine the maximum order p in AR (p). Because the ACF and PACF results obtained values that fall close to zero after the first lag, then the estimation of the ARIMA model is ordered 1 [10]. Then from the order, it is possible to estimate several possibilities of the ARIMA model including ARIMA (1,1,0); ARIMA (0,1,1); and ARIMA (1,1,1); Furthermore, the three estimates of the model estimation were tested for parameter significance based on the output in Minitab 17. Estimation Result ARIMA Model and Significant Test can be seen in the Table 9.

Table-9: Estimation Result ARIMA Model and Significant Test

No	Model	Type Model	T Statistic Value	p-value	Significant
1	ARIMA (1,1,0)	AR 1	-3.46	0.002	Significant
		Constant	-1.21	0.236	Non-Significant
2	ARIMA (0,1,1)	MA 1	10.27	0.000	Significant
		Constant	-8.84	0.000	Significant
3	ARIMA (1,1,1)	AR 1	-0.88	0.386	Non-Significant
		MA 1	3.73	0.001	Significant
		Constant	-3.16	0.004	Significant

Sources: UN Comtrade, 2018 (data processed)

Statistical parameter tests can be done using statistics or value P-value. Using statistics requires a statistical table, while P-value can be concluded without having to look at the P-value table because it is sufficiently compared to the tolerance level (α) to test the hypothesis. If the values $P<\alpha = 0.05$, the autoregressive (AR) or moving average (MA) parameters are quite significant in the model [10]. After testing the parameters by looking at the p-value, it is necessary to proceed with another test, namely the residual test to see the residual value of each model.

Residual Test

Residual independence test uses the Chi-Square (α) and Ljung-Box-Pierce statistical values. The assumption of residual independence is fulfilled if the Ljung-Box-Pierce statistical value is less than the Chi-Square (α) statistical value [10]. However, the results of the Ljung-Box-Pierce test output obtained an undefined result in the residual value of both the Chi-Square value, and also the p-value in the three ARIMA models.

Selection of Models Forecasting

From the results of the two tests namely parameter significance test and residual test, it can be concluded that the ARIMA model (0,1,1) is the most appropriate model and meets the required assumptions. Based on statistical parameter estimation test, the two P-value of the ARIMA (0,1,1) model, namely P-value of MA (1) of 0.000 (significant) and constant of 0.000 (significant) which are smaller than the value of $\alpha = 0.05$ [4]. So that in the ARIMA (0,1,1) model is selected as a model in the ARIMA model used.

Forecasting Accuracy Measurement

The accuracy of forecasting is an important factor in deciding among various alternative forecasting methods. The accuracy of a forecast is based on the results of historical errors of forecast (error).

The results of the calculation error forecasting on each forecasting model based on Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), and Mean Square Error (MSE) can be seen in the Table 13.

Table-13: MAPE, MAD, and MSE in Each Forecasting Model

No	Forecasting Model	Accuracy Measurement		
		MAPE	MAD	MSE
1	Moving average: - Length 3 years	1.3964E+01	6.09773E+06	7.04805E+13
2	Single Exponential smoothing: - Alfa =0.2 - Alfa =0.5 - Alfa =0.9	1.88003E+01 1.35600E+01 1.30686E+01	7.50754E+06 6.14109E+06 6.25154E+06	9.07836E+13 7.63807E+13 1.02766E+14
3	Least Square Trend	1.15509E+01	5.40161E+06	5.71138E+13
4	Quadratic Trend	1.09025E+01	5.05006E+06	5.13219E+13
5	ARIMA	1.09023E+01	5.05001E+06	5.13216E+13

Sources: UN Comtrade, 2018 (data processed)

Based on the results of the recapitulation of the three measures of forecast error in Table 13, one of the best models is obtained and the smallest forecast error is close to zero, Box-Jenkins (ARIMA) is the best model for predicting the Indonesia's shrimp export with MAPE is 1.09023E+01, MAD method is 5.05001E+06, and MSE is 5.13216E+13.

Forecasting of Indonesia's Shrimp Export with the Best Model

Based on the forecasting of the five quantitative model and through the measurement of forecasting errors, The ARIMA model with the ARIMA (0,1,1) version is the best because it has P-value of MA (1) of 0.000 (significant) and constant of 0.000 (significant) which are smaller than the value of $\alpha = 0.05$. The forecasting results of Indonesia's shrimp export to Japan for the next period can be seen in the Figure 16.

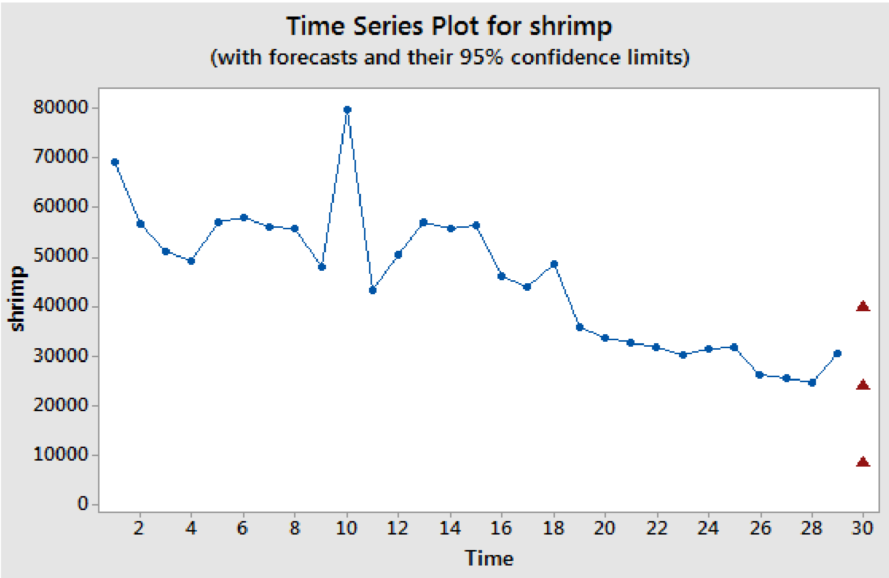

Fig-16: Graph of forecasting Indonesia's Shrimp Export with the Best Model

Based on the Figure 16, it can be seen that the results of forecasting Indonesia's shrimp exports to Japan using the ARIMA model (0.1,1) show the forecasting in 2018 is 24,213,800 Kg with lower limit of 8,410,550 Kg and upper limit of 40,017,000 Kg which decreased actual exports in 2017 is 25,425,700 Kg.

Implications of Results

The results showed that the best forecasting model and the right one to predict for Indonesia's Shrimp Export was the Box-Jenkins model or ARIMA model with the ARIMA (0,1,1) variety. This model produces predictions that are more accurate than other models because it has the smallest forecast error or close to zero.

ARIMA model is a fairly complicated model compared to other time series forecasting methods. Although classified as a complex stage, this model has the advantage of being able to predict more accurately or approach actual value than other models. ARIMA forecasting model is also more suitable to be used in Indonesia's Shrimp Export data because it corresponds to the characteristics of the data used. The ARIMA model is used to predict stationary data in variance and stationary in average. If the data is not stationary in variance, it needs to be transformed first, whereas if the data is not stationary in the average, differentiation is done.

Forecasting results with the best model can be used as a reference in decision making related to raw material management and production and financial management. The future Indonesia's shrimp export forecast can be used as a guideline in making policies in planning and procurement of shrimp raw material inventories. This is done to support the planning and implementation, especially for Indonesia's Shrimp Export.

CONCLUSION

The results of Indonesia's shrimp exports to Japan for period 30 of 2018 with Moving Average model 3 period are 27,080,419 kg. Single Exponential Smoothing Model with smoothing coefficient α = 0.2; α = 0.5 and α = 0.9, respectively is 30,942,641 kg; 28,444,131 kg; and 30,191,341 kg. Forecasting with Least Square Trend model is 27,101,974.88 kg. Forecasting with Quadratic Trend Model is 19,089,500 kg, and forecasting with ARIMA model (0,1,1) is 24,213,800 kg.

The results of the recapitulation of the forecasting errors, obtained the best model is Box-Jenkins (ARIMA) model with the ARIMA model (0,1,1) which has the smallest forecast error or close to zero. The ARIMA (0,1,1) model has the smallest forecasting error that is MAPE of 1.09023E+01; MAD is 5.05001E + 06; and MSE is 5.13216E + 13. So it can predict more accurately than other forecasting methods. The forecasting results of Indonesia's shrimp exports with ARIMA model (0,1,1) show the forecasting in period 30 is 24,213,800 kg.

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