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Forecasting Palm Oil Prices in Malaysia by Using Neural Network Model and Box-Jenkins Model

Eng Yun Shun, Shariffah Suhaila Syed Jamaludin*
Department of Mathematical Sciences, Faculty of Science, Universiti Teknologi Malaysia
*Corresponding author: suhailasj@utm.my

Abstract
Palm oil industry developed globally as time varies. The fluctuation of palm oil prices would affect the economy in Malaysia. The objective of this study is to examine the patterns of palm oil prices. The extensive techniques used to predict palm oil prices are Artificial Neural Network (ANN) Model and Box-Jenkins (ARIMA) Model. The significance of this study is to assist in analyzing the trend of future palm oil prices and reduce risk. This study uses monthly prices of palm oil from January 1995 until December 2021. The findings of this study show that ARIMA (0,1,4) is the best model based on the lowest values of the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) which are 3338.416 and 3356.276 respectively. Meanwhile, ANN (4-8-1) with 1000 repetitions has the lowest MSE (0.001379) among the others network. The performance of both chosen models is measured by calculating the error measurements of Mean Percentage Absolute Error (MAPE), Mean Absolute Error (MAE), and Root Mean Absolute Error (RMSE). The ANN (4-8-1) model is chosen as the forecasting palm oil prices approach because it has the lowest error measurements of MAE (96.8592), MAPE (4.4012), and RMSE (130.1014) compared to ARIMA (0,1,4).

Keywords: Palm oil prices; ARIMA; ANN; forecast

1. Introduction

Over the past 50 years, the palm oil market become widely developed throughout the world. The two largest producers of palm oil are Indonesia and Malaysia. According to Ashaari et al. (2022), Malaysia accounted for 25.8% and 34.3% of the world's palm oil production and export respectively. Palm oil is one of the major economic commodities in Malaysia since it contributed 37.7% of the Growth Domestic Product (GDP) to the agricultural sector in Malaysia in 2020 (Ashaari et al., 2022). There have more than half a million employees in the palm oil industry and supports the livelihood of almost one million people (Parveez et al., 2022). It is one of the main income-generating industries in Malaysia. Hence, forecasting palm oil prices is able to avoid unnecessary losses or risk associated. Nevertheless, palm oil is the most widely-used vegetable oil in the world. It has various functions that can be used by food and non-food manufacturers because of its functional benefits, versatility, and widespread availability.

The prediction of the palm oil market is significant for stakeholders such as governments, public and private enterprises, and investors so that they can have the proper planning and decision-making. Future prediction of the palm oil market allows investors to invest at a predetermined price in order to minimize the risks associated with volatility in the prices. The palm oil industry in Malaysia experiences fluctuation in prices because of several factors such as supply, demand, and social factors that make changes in the world economy (Shakawi, 2021). Two extensive model techniques were conducted in this study which are Artificial Neural Network (ANN) Model and Box-Jenkins Model. ANN model is a mathematical model based on biological neural networks and it has the ability to be used as an arbitrary function approximation mechanism that 'learns' from observed data (Shaaib, 2015). The neural network consists of neurons and it was organized into layers and served as a model of the path like the human brain processes information. Box-Jenkins model is a mathematical model designed to predict data based on the inputs from specified time series. Box-Jenkins model is synonymous with the Autoregressive Integrated Moving Average (ARIMA) model. The ARIMA model has the techniques of analyzing to forecast the data by using three principles such as autoregression, differencing, and moving average. It can revise the historical data in order to make predictions.

The purpose of this study is to examine the fluctuation of palm oil prices and analyzing the historical data of the monthly palm oil prices from January 1995 to December 2021 in Malaysia. Thesample data are divided into two categories which are training data (January 1995 to December 2016) and testing data (January 2017 to December 2021). This study is to evaluate and compare the efficiency of forecasting methods: ANN and ARIMA with the smallest error measurement which indicates higher accuracy. The performance of the forecasting models will be evaluated by using the Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE).

The Box-Jenkins (BJ) approach has become one of the most popular methods for time series forecasting because it usually presents good results. Previously, there have been several studies conducted on forecasting palm oil prices by using Box-Jenkins's method. For instance, a study was conducted by Nochai & Nochai (2006) to forecast oil palm prices (farm price, wholesale price, and pure oil price) in Thailand from the year 2000 to 2004. It concluded the three most appropriate ARIMA models for each type of oil palm prices in order for forecasting purposes because of the minimum MAPE. Apart from the BJ approach, Neural Networks (NN) also has been widely used in different fields such as industry, science, business, and so on especially time series forecasting because it serves as an alternating tool for both forecasting researchers and practitioners (Ismail & Khamis, 2011). Karia et al. (2013) found that the most appropriate model to forecast the CPO prices in the study is ANN because it fits the results well followed by Autoregressive Fractionally Integrated Moving Average (ARFIMA) and Adaptive Neuro-Fuzzy Inference System (ANFIS). Besides, neural networks are 'trained' using the backpropagation algorithm. It can determine the values for parameters in order to achieve better-predicted outputs. The neural network consists of three layers: an input layer, a hidden layer, and the output layer. The input layer nodes work as a receiver to receive information from the independent variables and then pass it to hidden layer nodes by multiplying weights, adding biases, and converting to output layer nodes. Hence, ANN applied widely in the prediction approach.

This study contributes knowledge regarding the approach of forecast methods on palm oil prices so that researchers or mathematicians can further investigate the modification of the methods. This paper is arranged as follows. The ARIMA model will be presented in Section 2. In the subsequent section, the method of the ANN model is reviewed. The experimental analysis and the results obtained are discussed in Section 4. The last section contains conclusions and suggestions for future research work.

2. Materials and methods

This study evaluates and predicts the price of palm oil prices using two approaches: ARIMA and ANN approach. This study uses monthly prices of palm oil in Malaysia from January 1995 until December 2021. The accuracy of the methods be tested by calculating the error measurements of mean absolute percentage error (MAPE), root mean square error (RMSE), and mean absolute error (MAE).

Model 1: ARIMA Model

The Box-Jenkins technique consists of four-iterative main procedures such as model identification, model estimation, model diagnostics, and forecasting (Ramesh, 1995).

Stationarity Testing

Stationary is a fundamental property required to be fulfilled. Otherwise, differencing must be used to convert the non-stationary series into stationary series. There are two methods to check stationarity.

a) Visualizations
The stationarity of the data can be checked by visualizing the plotted graph of the time series plot and ACF plot. From the time series plot, it is stationary if the series fluctuates around the means or cuts off fairly quickly. The series is non-stationary if the ACF decays very slowly from the ACF plot. Differencing is done until the data varies about a fixed level, and the graph of ACF either cuts off fairly quickly or dies down fairly quickly.

b) Augmented Dicker-Fuller (ADF) test
Apart from visualization of the plotted graphs, the Augmented Dicker-Fuller (ADF) test can also be used to support the decision-making of stationarity. The hypothesis of the ADF test (Mohamed, n.d.) is shown as:

H_0 : The series is non-stationary

H_1 : The series is stationary

If the p-value is greater than the significance level (α), it indicates that H_0 unable to be rejected and the data needs to be differenced to make it stationary. Otherwise, H_0 is rejected if the p-value is smaller than the significance level (α) and the series is stationary and doesn't need to be differenced.

Differencing
If the time series is not stationary, the transformation process will be applied to achieve stationary. The stationary series W_t obtained as the d^{th} difference Δ^d of y_t
General equation:

$$W_t = \Delta^d y_t = (1-\beta)^d y_t \quad (1)$$

where y_t = observation from the series at time *t*,
y_{t-1} = observation from the series at time $t-1$
β = backshift notation,
W_t = stationary series

Model Identification
Model identification refers to the methodology in identifying the required transformation and the orders of *p* and *q* for the model. The data are used to plot the graphs and identify the parameters by visual inspection of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). The MA (*q*) time series has an autocorrelation function (ACF) that has a cut off after *q* lags while the partial autocorrelation function (PACF) has cut off after *p* lags occurred for the AR (*p*) time series.

Table 1: Properties of ACF and PACF (Paretkar et al., 2008)

Process	ACF	PACF
AR (p)	Tails off towards zero (exponential decay/damped sine wave)	Cut off to zero after order p
MA (q)	Cut off to zero after order q	Tails off towards zero (exponential decay/ damped sine wave)
ARMA (p, q)	Tails off towards zero (exponential decay/damped sine wave)	Tails off towards zero (exponential decay/damped sine wave)

Model Estimation & Selection
The model estimation process is to find the best possible estimation for the parameters. There have various techniques such as trial and error, maximum likelihood methods, least squares method, and so on to determine the coefficients and estimate the ARIMA model. The technique of trial and error conducted in this study is to examine different values of the parameters. Then choose the value that minimizes the sum of squared residuals of fitting the model.

Moreover, the next step is the model selection process. There are two tests such as Akaike's Information Criteria (AIC) and Bayesian information criterion (BIC) will be carried out to check the adequacy and best-fit model for the datasets. A better-fit model should have smaller AIC and BIC values.

a) Akaike's Information Criteria (AIC)

$$AIC = n\left[\ln\frac{2\pi R}{n} + 1\right] + 2k \tag{2}$$

b) Bayesian information criterion (BIC)

$$BIC = n\left[\ln\frac{R}{n}\right] + k\ln(n) \tag{3}$$

where $k =$ number of estimated parameters in the model (excluding the white noise variance)
$= p + q + 1$ if the intercept is included
$= p + q$ if the intercept is not included
$n =$ sample size, $R =$ Residual sum of squares$= \sum_{i=1}^{n} \varepsilon_i{}^2$ where ε_i is residuals.

Diagnostics Model

After the parameters have been estimated, the following step is called model diagnostics. The statistical tests (ACF and PACF residuals) and the Ljung-Box Chi-Square test were used to make verifications of the model.

a) ACF and PACF residual plots
The model with no significant autocorrelations or spikes at any lag order in the ACF and PACF residual plots is considered a proper fitting model.

b) Ljung-Box Chi-Square test
The test is used to check for a model with a lack of fit and test the hypothesis for the randomness of the series. The model is considered adequate if the *p*-value associated with the statistics is large (*p*-value > α). Otherwise, it is not adequate. If the model is valid for verification, then the model can be ready to be used to forecast future values, otherwise repeat the steps of identification, estimation, and diagnostics until a satisfactory model is generated. The following is the hypothesis of the Ljung-Box Chi-Square test:

H_0 : The series is random (does not show lack of fit: Adequate)

H_1 : The series is not random (show lack of fit: Not Adequate)

The null hypothesis, H_0 is rejected if $\chi^2{}_m > \chi^2{}_{1-\alpha, df}$
where $\chi^2{}_{1-\alpha, df} =$ value of Chi-square distribution for a significance level, α and df degree of freedom.

When the Ljung-Box Chi-Square test is applied to residuals of the ARIMA model, the degree of freedom *df* is equal to $df = m - p - q$ where *p* and *q* are the order of autoregressive and moving average respectively.

Forecasting

The adequate model with minimum values of both AIC and BIC is chosen to be used in forecasting.

Model 2: ANN Model

Artificial Neural Network (ANN) is a non-linear mathematical model that reveals the inputs and outputs of data. The neural network consists of three layers: an input layer, a hidden layer, and the output layer. The input layer nodes work as a receiver to receive information from the independent variables and then pass it to hidden layer nodes by multiplying weights, adding biases, and converting to output layer nodes.

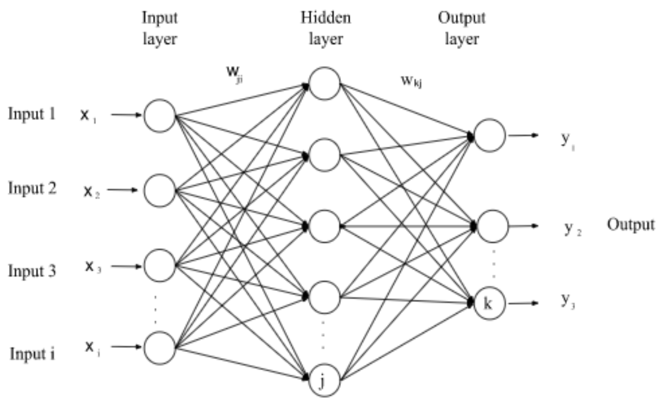

Figure 1 General Feedforward ANN model.

Normalization Process

Normalization is a technique used in data preprocessing to standardize the feature exits in the dataset to a specific range. It eliminates the influence of one feature on another feature by transforming all features in the dataset to a fixed range to give equal importance to all the features. The data is divided into 80:20 which indicated that 80% of the data is used to train the neural network while the remaining 20% of data is used as testing data to make predictions. The min-max function produces output in the range (0,1) for a given input value.

The normalization for the input is done by using the formula (A. Victor Devadoss & T. Antony Alphonnse Ligori, 2013,):

$$x_N = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (4)$$

where x denotes the values to be normalized; x_N denoted the normalized value of x; x_{min} represents the minimum value of x; x_{max} represents the maximum value of x.

Activation Process

The activation function is to adjust the weights of neural networks. The nonlinear transfer function for a neuron used is sigmoid which is to transform any real number to the range between 0 and 1. It is expressed as

$$f(x) = \frac{1}{1 + e^{-cx}} \quad (5)$$

where $c =$ constant (c tends to infinity the sigmoid approximates a threshold function), $x =$ input

Multilayer perceptron (MLP)

The MLP is a type of feedforward artificial neural network consisting of at least three layers of nodes. Each neuron in both the hidden layers and the output layer uses a non-linear activation function. It is a back propagation network that consists of the input layer, the hidden layer, and the output layer. The input layer nodes receive information from independent variables and pass them to the hidden layer nodes by multiplying them by weights and adding biases, which they convert through the sigmoid nonlinear activation function. Then, pass to the output layer nodes, which turn it into a linear activation function (Sahed & Toul, 2021). The neural network is repeatedly trained several times to obtain the optimal number of neurons in hidden layers with minimum MSE.

Forecasting Model Evaluation

The error measurements such as Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) are necessary to evaluate the accuracy of the forecasting models. An outperformed model must have the least error.

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{y_t-\widehat{y_t}}{y_t}\right| \quad (6)$$

$$RMSE = \sqrt{\sum_{t=1}^{n}\frac{(y_t-\widehat{y_t})^2}{n}} \quad (7)$$

$$MAE = \sum_{t=1}^{n}\frac{|y_t-\widehat{y_t}|}{n} \quad (8)$$

where y_t = actual value at time *t*, $\widehat{y_t}$ = predicted value at time *t*, n = sample size

2. Results and discussion

ARIMA Model

The data of palm oil prices in Malaysia from January 1995 to December 2021 is non-stationary since it has a linear upward trend as shown in Figure 2 while Figure 3 shows the ACF plot decays extremely slowly as time varies. The series does not fulfill the stationary conditions. The existence of a trend necessitates transforming the data into its logarithmic form and differencing the series.

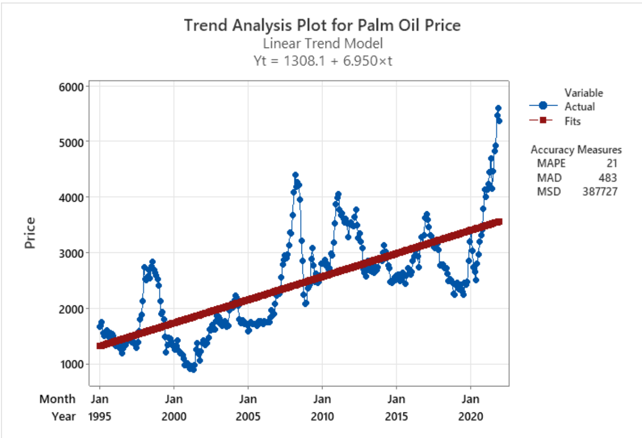

Figure 2 Trend Analysis plot of Palm Oil Prices in Malaysia (1995-2021)

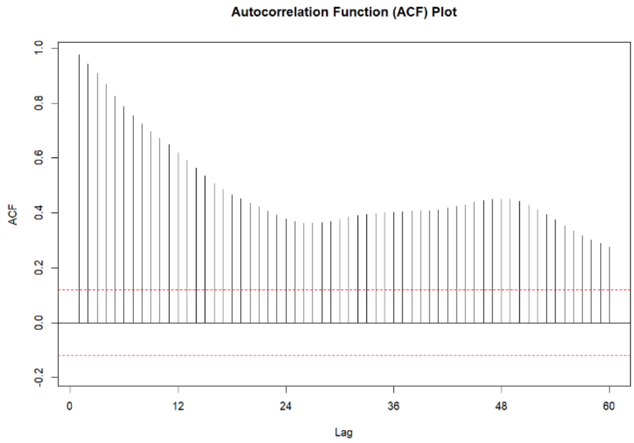

Figure 3 ACF plot for Palm Oil Prices

The ADF test show that the p-value is 0.1447 which is greater than the 5% significance level. Hence, the null hypothesis cannot be rejected which indicates that the data is not stationary.

Table 2: ADF Test of series

```
        Augmented Dickey-Fuller Test

data:  Training_Data
Dickey-Fuller = -3.0238, Lag order = 6, p-value = 0.1447
alternative hypothesis: stationary
```

After the first differencing, the series fluctuates around the mean (Figure 4).

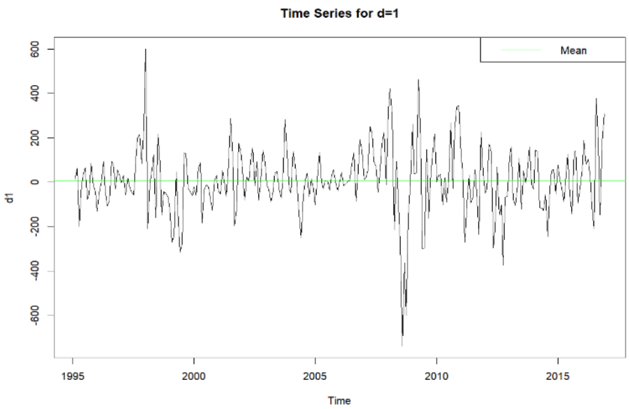

Figure 4 Trend Analysis for first order differencing ($d = 1$)

Figure 5 and 6 indicates that the autocorrelation (ACF) plot and partial autocorrelation (PACF) plot after first order differencing. The ACF plot of 1^{st} differencing cuts off or dies down quickly after lag 1. It has a significant spike at lags 1,4 and 6 whereas the PACF plot after the first order differencing that has a significant spike at lags 1 and 5 only.

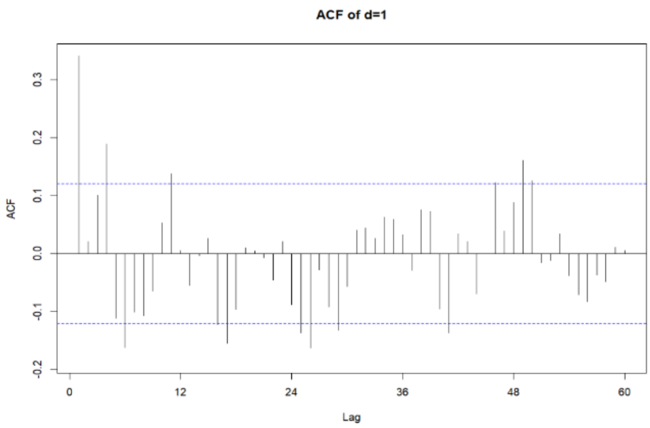

Figure 5 ACF plot after first order differencing

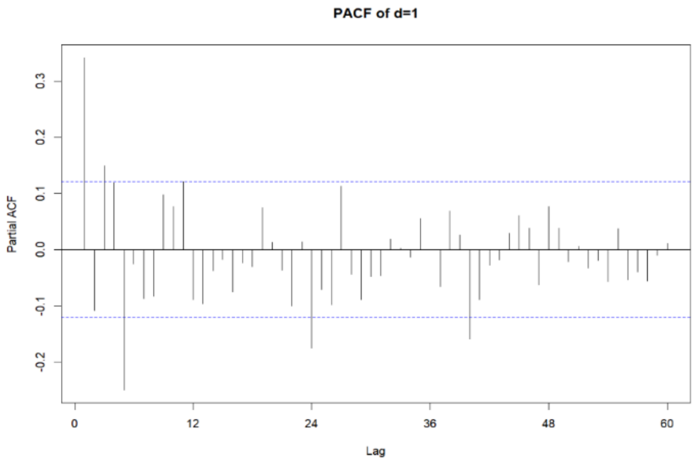

Figure 6 PACF plot after first order differencing

From the ADF test (Table 3) shows a p-value of 0.01 which is smaller than the 5% significance level. Hence, the series become stationary after the first differencing.

Table 3: ADF Test of differenced series ($d = 1$)

```
        Augmented Dickey-Fuller Test

data:  d1
Dickey-Fuller = -6.565, Lag order = 6, p-value = 0.01
alternative hypothesis: stationary
```

Model Identification Process

The ACF plot identifies the possible MA (q) terms; the PACF plot identifies the possible AR (p) terms. In the identification process, the table below shows the eight possible ARIMA models:

Table 4: Possible ARIMA Models for Palm Oil Prices

ARIMA (*p*,*d*,*q*) Model			
(0,1,1)	(1,1,0)	(3,1,0)	(5,1,0)
(0,1,4)	(1,1,1)	(3,1,1)	(5,1,1)

Model Selection and Estimation Process

The parameter was estimated through trial and error approach and the AIC and BIC was calculated for the ARIMA models. The best model is ARIMA (0,1,4) since it has the smallest values of AIC and BIC as compared to the other models.

Table 5: Comparison of ARIMA models

ARIMA(*p*,*d*,*q*) Model	r	AIC	BIC
(0,1,1)	1	3358.778	3365.992
(0,1,4)	4	3338.416	3356.276
(1,1,0)	1	3362.652	3369.796
(1,1,1)	2	3360.452	3371.168
(4,1,0)	4	3355.637	3373.497
(4,1,1)	5	3349.746	3371.179
(5,1,0)	5	3340.150	3361.583
(5,1,1)	6	3341.612	3366.617

Diagnostics Model

The randomness of the residuals to be tested by using Ljung–Box Statistics. If the *p*-value is less than 0.05 significance level, hence it is considered as not adequate; otherwise, it is adequate. From all 8 ARIMA models, only three models are adequate and can be used to model the data. ARIMA (0,1,4) will be used to check for the diagnostic test. The ARIMA (0,1,4) shows a *p*-value equal to 0.0780 which is greater than the 0.05 significance level. Hence, the null hypothesis could not be rejected. The model is considered adequate.

Table 6: Summary of Q-Statistics for Arima Models

ARIMA(*p,d,q*) Model	**Summary of Q-statistics**	**Adequacy**
(0,1,1)	0.0008 ($p<0.05$)	Not Adequate
(0,1,4)	0.0780 ($p>0.05$)	Adequate
(1,1,0)	0.0001 ($p<0.05$)	Not Adequate
(1,1,1)	0.0005 ($p<0.05$)	Not Adequate
(4,1,0)	0.0004 ($p<0.05$)	Not Adequate
(4,1,1)	0.0055 ($p<0.05$)	Not Adequate
(5,1,0)	0.1262 ($p>0.05$)	Adequate
(5,1,1)	0.0816 ($p>0.05$)	Adequate

Table 7: Ljung-Box test of ARIMA (0,1,4) model

```
        Ljung-Box test

data:  Residuals from ARIMA(0,1,4)
Q* = 29.522, df = 20, p-value = 0.07798

Model df: 4.   Total lags used: 24
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Artificial Neural Network (ANN)

Data Normalization

The min-max normalization function is applied to produce the output within the range (0,1) for a given input value.

$$x_N = \frac{x-889.2}{3499.66-889.2} = \frac{x-889.2}{2610.46} \tag{9}$$

Activation Process

After the normalization of the data, the network utilizes the dynamic back propagation model and implements a sigmoid function as the activation function. According to the MSE results obtained, the network with 4 input neurons, 8 hidden neurons, and one output neuron with repetitions of 1000 has the minimum error which is 0.001379. The data was trained 1000 times tend to obtain more accurate results. After the MLP process, used the most appropriate network, (4-8-1) to forecast the palm oil prices.

Table 8: Results of Mean Square Error (MSE)

Input Neurons	Hidden Neurons	Repetitions of 250	Repetitions of 500	Repetitions of 1000
4	8	0.001382	0.001381	0.001379

Evaluation of Forecasting Model

Based on the calculated results obtained, ANN has lower values of MAE, MAPE, and RMSE which are

96.8592, 4.4012, and 130.1014 respectively as compared to the ARIMA model. Hence, ANN has the best performance that can be used to make predictions of palm oil prices.

Table 9: Summarize performance of best ARIMA and ANN

Models	MAE	MAPE	RMSE
ARIMA (0,1,4)	98.4755	4.5232	135.0455
ANN (4-8-1)	96.8592	4.4012	130.1014

Based on the graph comparison between actual palm oil price and forecasting price for the ARIMA model and ANN model, the ANN model shows better forecasting performance as it is more closer to the actual price.

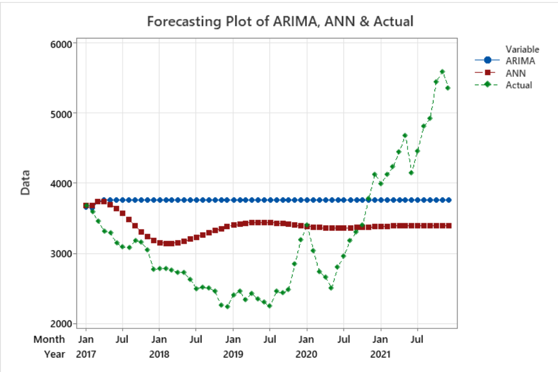

Figure 7 Forecast Plot of Arima, ANN, and Actual Palm oil prices (2017-2021)

Conclusion

In this paper, the ANN model constructed better performance than the ARIMA model since the ANN model demonstrates lower values of the error measurements. This is due to it having the ability to learn from data and go through hidden layers which are to transform it into output while the ARIMA model only uses the past and the present of price and has poorer performance for long-term forecasts. The findings in this study conclude that the ANN method was better applied for forecasting palm oil prices. Therefore, in future research, the number of input neurons should be increased to improve the results. It is recommended that future research can apply hybrid forecasting methods of statistical and machine learning methods for predictive analysis.

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