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THE PERFOMANCE OF THE ARIMAX MODEL ON COOKING OIL PRICE DATA IN INDONESIA

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ABSTRACT

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Forecasting is crucial for planning, particularly in addressing potential issues. While ARIMA models are commonly used for time series forecasting, they may need more accuracy by overlooking external factors. The ARIMAX model, which incorporates exogenous variables, is employed to enhance accuracy. This study applies the ARIMAX model to forecast cooking oil prices in Indonesia, known for its complex patterns. Using data from the Directorate General of Domestic Trade and Price Stability (2024), the research highlights fluctuating cooking oil prices from 2010 to 2023 every month. Both ARIMA and ARIMAX models are utilized, with domestic fresh fruit bunch (FFB) prices and the COVID-19 pandemic indicator as exogenous variables. Evaluation based on Mean Absolute Percentage Error (MAPE) shows that the ARIMAX model has a MAPE of 17.31%, compared to 17.69% for the ARIMA model. The lower MAPE value for ARIMAX indicates improved forecasting accuracy by incorporating external factors. Thus, the ARIMAX model is recommended for predicting cooking oil prices, offering better accuracy and valuable insights for policymakers and stakeholders.

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1. INTRODUCTION

Forecasting plays a crucial role in future planning, enabling decisions to be made now to anticipate potential problems that may arise in the future. One commonly used method is time series analysis, which uses historical data to predict future trends or patterns. Various time series models can be applied to single or univariate data for this forecasting [1]. The model that is often applied to time series data with one variable is the Autoregressive Integrated Moving Average (ARIMA) model. ARIMA forecasts time series data by using past values and present values as exogenous variables. However, in some cases of time series data, it is influenced by factors other than time factors, so the ARIMA model is not able to explain the data pattern. The ARIMAX forecasting model can be used because it considers other factors besides time as exogenous variables. The ARIMAX model is used in some situations to make the ARIMA model more accurate. The ARIMAX model (Autoregressive Integrated Moving Average with Exogenous Model) is thought to capture specific patterns by including information about certain events as additional variables or exogenous variables [2]. One example of time series data is cooking oil price data, often the focus of policymakers' discussions.

Modeling cooking oil price data is essential because cooking oil is one of the basic needs of Indonesian people. Recently, cooking oil prices have often shown complex patterns due to extreme upward and downward fluctuations that are irregular and difficult to predict. Since the government announced the first COVID-19 case in Indonesia on March 2, 2020, several goods prices have soared uncontrollably [3]. Data from the Directorate of Food Supply and Price Stabilization, Deputy for Food Availability and Stabilization (2024), shows that the price of packaged cooking oil in 2023 experienced a downward trend. However, from the end of 2023 to 2024, the price of packaged cooking oil experienced a slight upward trend [4]. The price situation for cooking oil became unstable after the emergence of the COVID-19 virus and notification from the government that this virus had been around since the beginning of March 2020, thus having an impact on various fields [5]. In 2022, the market will show a cooking oil shortage, soaring selling prices to Rp 40,000 per liter. The public reacts to long queues when there are government or private market operations, large purchases, and hoarding of cooking oil [6]. The government needs to pay attention to the unstable fluctuations in cooking oil because cooking oil is a strategic commodity primarily consumed by the public. This irregularity complicates analysis, especially when long time series data are involved. Cooking oil prices require a deep understanding of the essential characteristics of price movements and accurate forecasting of cooking oil prices. Cooking oil cannot be separated from the availability of the raw material, namely Crude Palm Oil (CPO), which significantly influences its price. The price of CPO is often volatile due to factors such as global demand, weather conditions, export policies, and production levels in key palm oil-producing countries like Indonesia and Malaysia. Fluctuations in CPO prices directly affect the cost of cooking oil, as CPO is a major component in its production. Therefore, understanding the dynamics of CPO prices is crucial in predicting future trends in cooking oil prices [7].

Forecasting cooking oil prices in Indonesia using a clustering approach with CID distance in ARIMA modeling is considered better for forecasting cooking oil prices than without clustering [8]. Forecasting the price of cooking oil in Pangkalpinang City using the exponential smoothing method with three basic methods such as the simple exponential smoothing model, the Holt exponential smoothing model, and the brown exponential smoothing model resulted in the Holt Exponential Smoothing model, providing the most accurate predictions for the price of cooking oil in Pangkalpinang City with RMSE value 1.18736. However, these methods do not account for the influence of external variables, which can lead to less accurate forecasts in volatile markets. The ARIMA and ARIMAX methods are suitable for forecasting with a MAPE value of less than 10% [9]. ARIMAX, with exogenous calendar variations, can improve the accuracy of total non-cash transaction predictions, both on in-sample data used to build the model and out-sample data to see the model's goodness in making predictions [10]. ARIMAX forecast results show pretty good results because the prediction results are almost the same as the original data [11]. ARIMAX is good to be used for forecasting 3, 12, and 24 months [12]. The ARIMAX model has a MAPE of 13.25%, which is better compared to the ARIMA model which has a MAPE of 13.35% in forecasting Export Load [13].

This research explores the application of the ARIMAX model to forecast cooking oil prices in Indonesia, incorporating exogenous variable such as crude palm oil prices and COVID-19. This approach has not been extensively explored in previous studies. By integrating these external factors, this study aims to provide a more accurate and reliable forecast, contributing to a better understanding of price movements and aiding policymakers in decision-making. Cooking oil price forecasts will provide relevant insight into future movements in cooking oil prices, which will be very useful for the government in decision-making and policy formulation. Apart from that, this information can also be used to anticipate and control possible events based on cooking oil price predictions by considering several factors.

2. RESEARCH METHODS

2.1 Data

The research was conducted using exogenous variables, namely the price of Palm Oil FFB (Fresh Fruit Bunches), obtained from the Directorate General of Plantations (Rupiah/kg), as well as dummy variables indicating the periods before COVID-19 (0) and after COVID-19 (1). The time series data used is the price of Indonesian cooking oil (Rupiah/kg) from 2010 to 2023 at monthly intervals. This data was obtained from the Central Statistics Agency through the Publication of Food Group Rural Consumer Price Statistics. Data collection on rural consumer prices for food groups was done through direct interviews with retail traders in rural markets. Enumeration is carried out every month on the 15th or the market day closest to the date. Three or four traders record the price of each commodity in each market. The price recorded is the price that appears the most (mode) or the average price. The data is divided into two parts: training and test data. Training data is used to develop forecasting models, while test data is used to forecast and evaluate the model's accuracy by comparing forecasting results with actual data.

2.2 Method

The research methods applied were ARIMA and ARIMAX. The ARIMA was a statistical modeling method to estimate possible future values between two predetermined limits. ARIMA combined elements of autoregressive and moving average models. In ARIMA analysis, all data was assumed to have "stationary" properties [14]. The ARIMAX (Autoregressive Integrated Moving Average Exogenous) model was an ARIMA model with additional variables [2]. This method was a forecasting method that considered independent variables. The following were the analysis stages in this research:

1. Preparing data on cooking oil in Indonesia and variables influencing it, such as the price of fresh fruit bunches and the COVID-19 pandemic variable. Then, divide the data into training data and test data;
2. Check stationarity by identifying time series data plots and ACF and PACF plots;
3. Carrying out differencing or transformation processes on data that is not yet stationary;
4. Establish ARIMA models through ACF and PACF plots;
5. Estimation and significance testing of parameters, as well as diagnostic examination;
6. Selection of the best ARIMA model with the most minor AIC criteria;
7. Identify each exogenous variable through a time series plot;
8. Modeling ARIMAX using the best model from ARIMA;
9. Estimation and significance testing of parameters, as well as diagnostic examinations;
10. Forecasting with the ARIMAX model;
11. Analyze the forecasting results using MAPE calculations to determine the accuracy level of the forecasting results that have been carried out on actual data and how the forecasting can follow the pattern of the actual data. The best model was determined by the smallest MAPE value.

MAPE (Mean Absolute Percentage Error) is a metric that shows the level of forecasting accuracy in percentage form. MAPE is more common because it is easier to understand (in percentage form). The smaller the MAPE value, the more accurate the forecasting results [15].

The following flowchart for this research used the ARIMAX model:

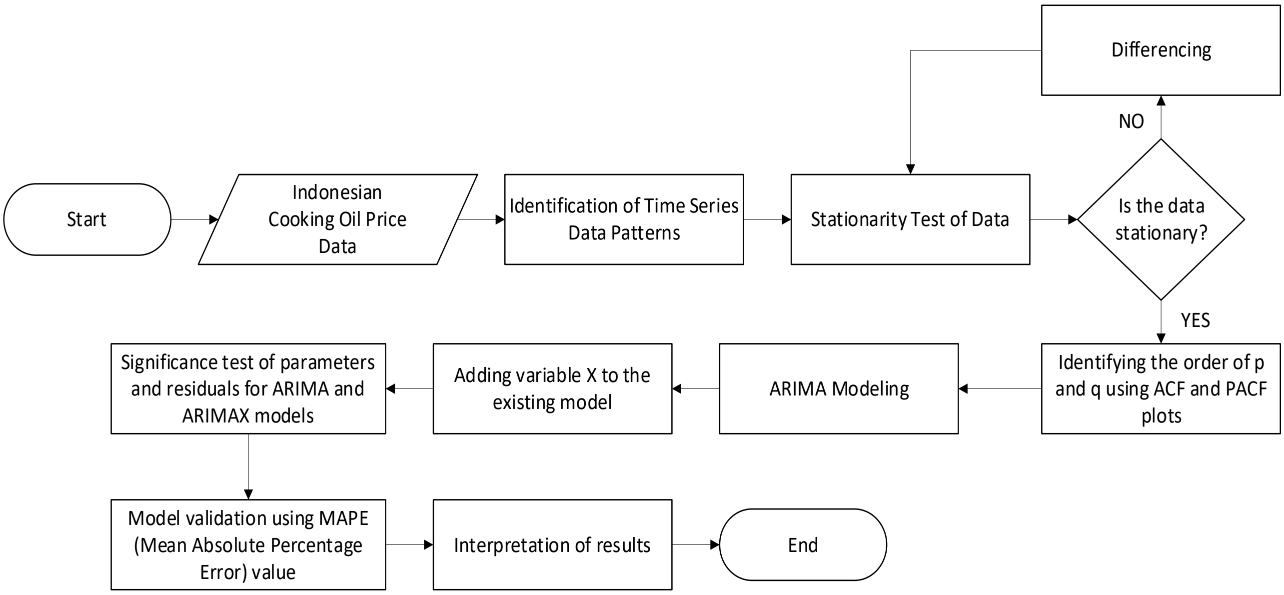

Figure 1. Research Flow Chart

3. RESULTS AND DISCUSSION

Plot time series data from Cooking Oil Prices (Rupiah) in Indonesia for 2010-2023 was presented in Figure 2. This plot provided a comprehensive overview of the trends and seasonal patterns observed within the data, highlighting significant fluctuations over the 14-year period. The visualization of this time series facilitated the identification of important patterns and structural breaks, which were essential for the subsequent modeling and forecasting processes.

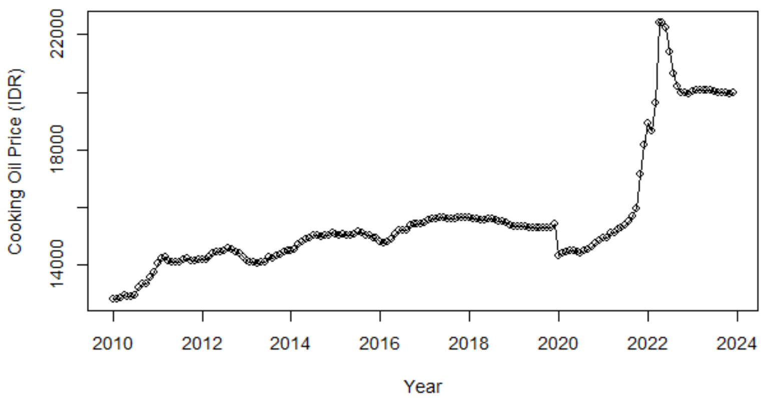

Figure 2. Time Series Plot of Cooking Oil Prices (IDR) in Indonesia January 2010-December 2023

It can be seen from Figure 2 that the data on cooking oil prices (Rupiah) in Indonesia from January 2010 to December 2023 shows a significant upward trend from 2021 to 2023. Prior to this increase, the data also indicated a notable decline in prices around late 2019, potentially due to economic interventions or shifts in global supply chains. This decline was followed by a sharp and sustained rise in prices starting in 2021. Then, the data was divided into training and test data to ensure the performance and generalization of the produced model. Data from January 2010 to December 2021 was used as training data to build the model, and data from January 2021 to December 2023 was used as test data to check the model's accuracy in predicting cooking oil prices in Indonesia. The graph of training data and test data is presented in Figure 3.

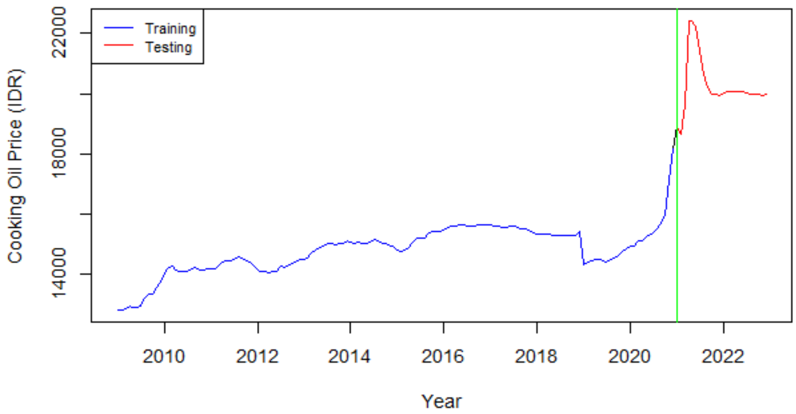

Figure 3. Time Series Plot of Training Data and Test Data of Cooking Oil Prices (IDR)

Identification of stationarity in training data was observed through time series plots and ADF tests. The training data graph in **Figure 3** indicated that the data pattern was trending and not stationary. From the results of the analysis, by performing one differentiation of the training data, it was found to be stationary when examining the ACF graph. The following is a graph of ACF and PACF data after making one differentiation, presented in **Figure 4**.

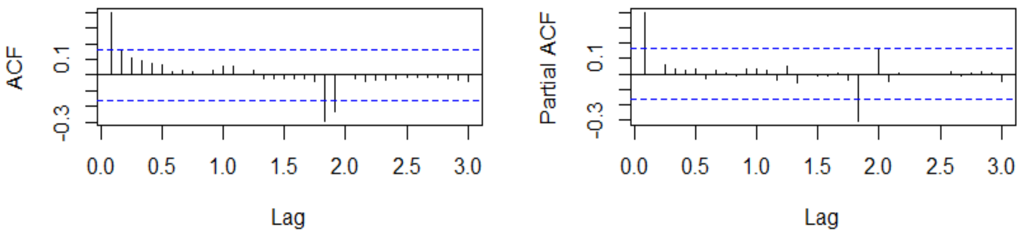

Figure 4. One Time Difference ACF and PACF Plots

Figure 4 showed that the ACF plot cuts off at lag two, indicating that the MA order was $q = 2$. The PACF plot from data that has been differentiated in **Figure 4** cuts off at lag one, indicating that the AR order was $p = 1$. Since differentiation was performed, d = 2. Five tentative models were considered for forecasting, namely ARIMA (1,1,1), ARIMA (1,1,2), ARIMA (0,1,1), ARIMA (0,1,2), and ARIMA (1,1,0). Model parameters, AIC values, BIC values, and model significance are presented in **Table 1**.

Table 1. ARIMA Model Identification

Model	Parameter	*p*-value	AIC	BIC	Significance of the Model
ARIMA(1,1,1)	$AR = 0.9210$	2.2×10^{-16}	1851.95	1860.84	Significant
	$MA = -0.4798$	0.000			Significant
ARIMA(1,1,2)	$AR(1) = 0.9406$	2.2×10^{-16}	1853.68	1865.53	Significant
	$MA(1) = -0.4904$	6.3×10^{-5}			Significant
	$MA(2) = -0.0618$	0.599			Not significant
ARIMA(0,1,1)	$MA = 0.3895$	4.9×10^{-9}	1864.86	1870.78	Significant
ARIMA(0,1,2)	$MA(1) = 0.4493$	3.2×10^{-8}	1860.71	1869.6	Significant
	$MA(2 = 0.2220$	0.011			Significant
ARIMA(1,1,0)	$MA = 0.5257$	2.2×10^{-10}	1855.47	1861.39	Significant

Based on the values in **Table 1**, the AIC and BIC values in the ARIMA model (1,1,1) were the smallest with significant parameter values. Therefore, the ARIMA model (1,1,1) was determined to be the best model. After testing the significance of the parameters, a diagnostic examination of the residuals from the formed model was conducted. The diagnostic examination included normality, heteroscedasticity, and white noise tests. The results of the diagnostic examination are presented in **Table 2**.

Table 2. ARIMA Model Diagnostic Check

Test Statistics	*p*-value	Decision
Ljung-Box	0.9031	Residual White Noise
Breusch-Pagan	0.9719	Homogeneous Residual Variety

Next, the overfitting model was checked with the selected ARIMA (2,1,1). However, the AR parameter (2) in the ARIMA model (2,1,1) was not significant, with AIC = 1853.68 and BIC = 1865.53, both of which were higher than the corresponding values for the ARIMA model (1,1,1). Since lower AIC and BIC values indicated a better-fitting model, the ARIMA (1,1,1) was preferred. Therefore, the ARIMA model (1,1,1) was proposed as the best model. Next, the formation of the ARIMAX model was carried out by adding exogenous variable to the model. The exogenous variables (X) used were X1 = domestic palm oil FFB price and X2 = Covid-19 pandemic variable (0 = before Covid, 1 = after Covid). The exogenous variables plotted in Figure 5. included the domestic palm oil FFB price (left) and the COVID-19 pandemic (right). The plot on the left showed the fluctuation of palm oil prices from 2010 to 2023, with a notable decline observed around **November 2019**. This decrease may have been caused by a combination of factors, such as reduced global demand and market adjustments leading up to the COVID-19 pandemic. Following this decline, the plot showed a sharp upward trend beginning in 2021, likely influenced by supply chain disruptions and increased demand during the pandemic. The plot on the right represented the COVID-19 pandemic variable, where the value of 0 indicated the pre-pandemic period and the value of 1 reflected the pandemic period, highlighting the pandemic's significant impact on palm oil prices.

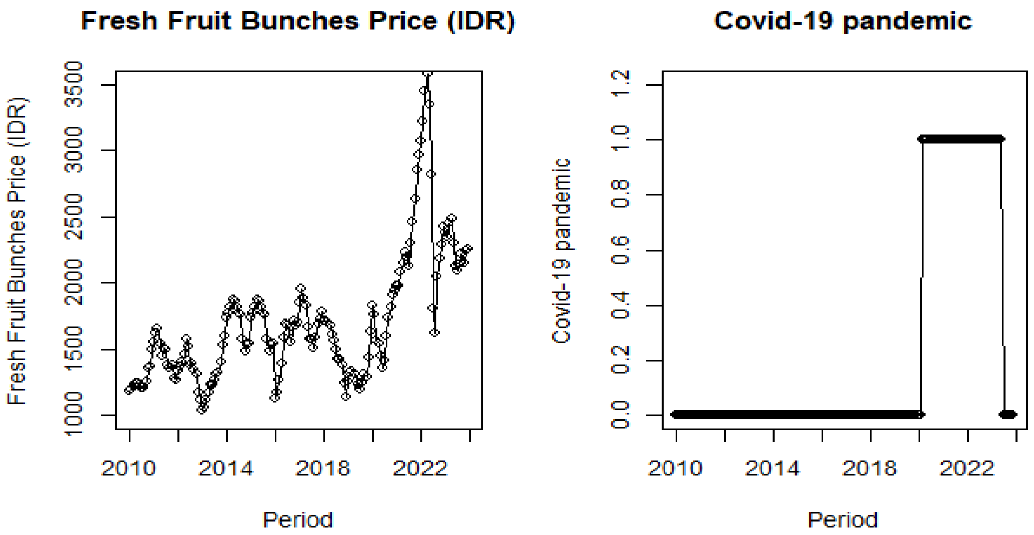

Figure 5. Plot of Exogenous Variables

The result of the correlation of exogenous variables with the response variable was presented in Table 3. The correlation results show that palm oil FFB price data has a strong correlation. The strong correlation between the price of Fresh Fruit Bunches (FFB) of oil palm and the price of cooking oil in Indonesia is due to the fact that FFB is the raw material in the production of crude palm oil (CPO), which is the primary ingredient for cooking oil. It is explained in the research [6] that as the price of CPO increases, the price of cooking oil becomes more volatile. In contrast, the pandemic effect has a moderate correlation with the price of cooking oil in Indonesia. The correlation between the effects of the pandemic in Indonesia is caused by panic buying, which has led to a shortage of cooking oil. This is mentioned in the research conducted by [16].

Table 3. Summary of Correlation Results

Case	Correlation	*p*-value
Indonesian Cooking Oil Prices vs. Effects of the Covid-19 Pandemic	0.5195	5.335×10^{-13}
Indonesian Cooking Oil Price vs Palm Oil FFB Price	0.7505	2.2×10^{-16}

The regression test showed that the price of palm oil FFB and the Covid-19 pandemic had an influence on the price of Indonesian cooking oil with an R-Square value of 0.9703 This indicated that 97.03% of the variation in Indonesian cooking oil prices could be explained by data on the price of palm oil FFB and the Covid-19 pandemic, while the remaining 3.37% was influenced by other variables. The model used to form the ARIMAX model was a tentative model from the ARIMA model, produced by adding variable X. Therefore, five ARIMA models were used. Model parameters, AIC values, BIC values, and ARIMAX model significance are presented in **Table 4**.

Table 4. ARIMAX Model Identification

Model	Parameter	p-value	AIC	BIC	Significance of the Model
$\boldsymbol{ARIMAX(1,1,1)}$	$AR(1) = 0.9258$	2.2×10^{-16}	1854.74	1869.55	Significant
	$MA(1) = -0.4993$	0.0000			Significant
	$X1 = 0.0860$	0.5619			Not significant
	$X2 = 146.14$	0.2986			Not significant

The ARIMAX (1,1,1) model was then subjected to a diagnostic test, and the results of the diagnostic examination were presented in **Table 5**. Next, an overfitting model was checked with the selected ARIMAX (2,1,1). However, parameters AR (2) in the ARIMAX model (2,1,1) were not significant with AIC = 1856.56 and BIC = 1874.33, which were still greater than the AIC and BIC values of the ARIMAX model (1,1,1). So, the ARIMAX model (1,1,1) was concluded to be the best model.

Table 5. ARIMAX Model Diagnostic Check

Test Statistics	p-value	Decision
Ljung-Box	0.9086	Residual White Noise
Breusch-Pagan	0.9652	Homogeneous Residual Variety

The next step was to calculate the forecasting value on the test data using the best model obtained. Forecasting uses the ARIMA (1,1,1) and ARIMAX (1,1,1) models on training data to determine how accurately the ARIMAX method could predict. The forecasting results obtained are shown in **Figure 6** below:

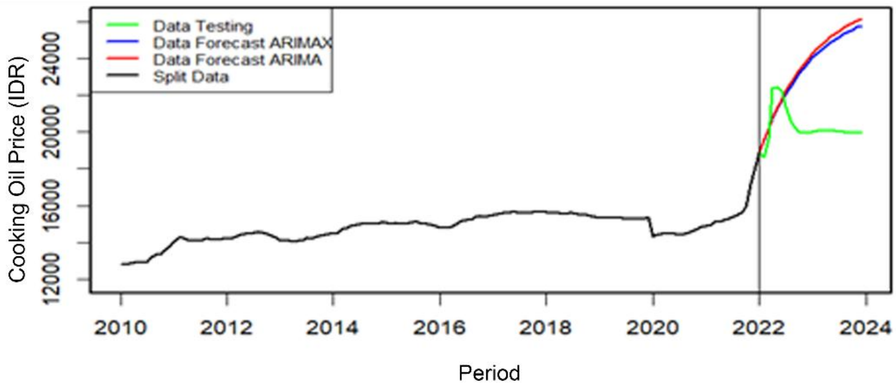

Figure 6. ARIMAX and ARIMA Forecast Charts

Figure 6 showed that the forecast results with the ARIMA and ARIMAX models werw almost identical, as indicated by the overlapping red and green lines. Model evaluation was conducted by examining the MAPE values presented in **Table 6**.

Table 6. ARIMA and ARIMAX Accuracy Table

MAPE ARIMA	MAPE ARIMAX
17.69 %	17.31%

The results of this research demonstrated that the ARIMAX model provided a more accurate prediction for cooking oil prices than the ARIMA model. This finding was consistent with the theoretical understanding that incorporating exogenous variables could enhance the predictive power of time series models [11]. By accounting for external factors such as crude palm oil prices and variation effects of the Covid-19, the ARIMAX model captured more of the complexity inherent in the price movements of cooking oil. The MAPE values obtained in this study align with these findings. The ARIMA model's MAPE value of 17.69% reflected its reliance on historical data without considering external influences, resulting in less accurate predictions. In contrast, the ARIMAX model's lower MAPE value of 17.31% demonstrates its ability to utilize additional information to refine its forecasts.

The lower MAPE value achieved by the ARIMAX model in this study demonstrated its superiority over the traditional ARIMA model for forecasting cooking oil prices. This aligned with existing theories and previous research, confirming that the inclusion of relevant exogenous variables could enhance the accuracy of time series forecasts. This research provided valuable insights for both academic and practical applications, suggesting that future studies should continue to explore and refine the use of exogenous variables in time series modeling to achieve more reliable predictions.

4. CONCLUSIONS

The ARIMAX model performs better than the ARIMA model in forecasting cooking oil prices. This is indicated by the lower MAPE value in the ARIMAX model (17.31%) compared to the ARIMA model (17.69%). The lower MAPE value in the ARIMAX model shows that adding domestic palm oil FFB price variables and the COVID-19 pandemic indicator as exogenous variables can provide more accurate forecasting results. Thus, the ARIMAX model is more recommended than the ARIMA model for forecasting cooking oil prices because the ARIMAX model can better capture external factors that influence cooking oil prices, resulting in more accurate forecasting.

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