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Application of ARIMA (Autoregressive Integrated Moving Average) model to predict Rupiah selling exchange rate against US Dollar

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Abstract

Currency is a tool in the form of money that is accepted and valid and legal as a payment and economic transactions in a country. US dollar is benchmark for world currencies, so predicting rupiah against US dollar is important. The purpose of this study is to analyze the characteristics of daily selling rate Rupiah against US Dollar, determine best model, and make predictions selling rate of Rupiah against US Dollar. Data used is daily data on selling rate of Rupiah against US Dollar 20 November 2020 - 19 January 2023 with details data training 20 November 2020 - 20 November 2022 and data testing 21 November 2022 - 19 January 2023. The model used is Autoregressive Integrated Moving Averages (ARIMA). The best model was chosen based on the smallest Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE) and Akaike Information Criterion (AIC). From the analysis results, it is found that best model is ARIMA (2,1,2) because it has significant parameters, white-noise residuals and has smallest MSE and MAPE values. With ARIMA model (2,1,2) the forecasting results for January 20 2023 – January 31 2023 is obtained with highest selling price on January 30 2023 Rp.15,932.4 and smallest on January 20 2023 Rp.15,901.9 and the average Rp.15,919.4. Based on these results, exporters and importers can consider their business activities.

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INTRODUCTION

Currency is a tool in the form of money that is accepted and valid and legal as a means of payment and economic transactions in a country. Each country has its own currency. Each currency has a different exchange rate or rate. The exchange rate is the price of a currency relative to another country's currency. Exchange rates play an important role in purchasing decisions because they allow us to translate prices from different countries into a common language (Ekananda, 2014). The exchange rate is very influential for a country in carrying out transaction activities outside the country. On August 14, 1997, the Government of Indonesia used a free-floating exchange rate system until now (Masri & Hadi, 2016), which means that exchange rates are allowed to fluctuate freely in response to changing economic conditions. This resulted in the exchange rate of the rupiah against the US dollar to be large.

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The rupiah exchange rate increases or decreases every day against the US dollar (Herawati, 2021). The currency used for comparison is the US Dollar because it is a strong currency. The fluctuation of the rupiah exchange rate against the US dollar has an impact on economic growth in Indonesia, for this reason, predicting the rupiah exchange rate against the US dollar is very important to do. One way to predict the rupiah exchange rate is to use ARIMA (Autoregressive Integrated Moving Average). In this study, predictions will be made of the rupiah exchange rate against the US dollar based on data on the rupiah exchange rate in previous years by determining the best model using the ARIMA. The advantage of using ARIMA model is that it can accept all types of data even though in processing, the data must be stationary first. This model is also quite accurate for short-term forecasting, but in long-term forecasting this model is less accurate because it tends to be flat.

The results of other studies regarding forecasting using the ARIMA model using daily data on the IHSG obtained quite accurate results with an absolute error of 2.6%. This study shows that the results of forecasting using the ARIMA model are not much different from the actual value. (Susanti & Adji, 2020). Another study uses daily stock data of PT. Telekomunikasi Indonesia, Tbk. The ARIMA model is used to predict the maximum and minimum stock prices for the period May-June 2011 using daily stock data for the period January 2010 - March 2011. In this study, the maximum and minimum prices for shares in the coming period are obtained (Hatidja, 2011). Another study used the ARIMA model with daily bitcoin data for the period January 10 2018 – March 10 2018. The results obtained from the research are that the price of bitcoin has decreased slowly in the coming period (Salwa et al, 2018). Based on the above background, the authors are interested in conducting research with the title "Application of the ARIMA Model to Predict the Rupiah Selling Exchange Rate Against the US Dollar".

The purpose of this study is to analyze the characteristics of the daily data selling exchange rate Rupiah against US Dollar 20 November 2020 – 20 November 2022 and determine the model and predict the selling rate of Rupiah against US Dollar 21 November 2022 – 31 January 2023 using daily data 20 November 2020 – 19 January 2023.

METHOD

Data

The data used in this study is secondary data obtained through the official website of Bank Indonesia, namely https://www.bi.go.id/. The data used is daily data on the Indonesian Rupiah exchange rate against the US Dollar on 20 November 2020 – 19 January 2023 with a training data period 20 November 2020 – 20 November 2022 and a data testing period 21 November 2022 – 19 January 2023.

Analysis steps

This study uses the ARIMA model and Minitab software in the process of data analysis. The following are the stages of the research that will be carried out:

1. Collection of research data. The data was obtained from the official website of Bank Indonesia and then input and processed to form a plot.
2. Identification of the ARIMA model, through data plots, ACF and PACF plots. General equation of ARIMA model is (Deviana et al, 2021):

$$\emptyset_p(B)(1-B)^d Y_t = \mu + \omega_q(B)\varepsilon_t \tag{1}$$

Identification is done by plotting ACF and PACF to determine whether the data is stationary or not. ACF is a correlation function that shows the relationship between the current time series (Y_t) and previous time observations (Y_{t+k}) and can be written (Wei, 2006):

$$P_k = \frac{cov(Y_t + Y_{t+k})}{\sqrt{Var(Y_t)}\sqrt{Var(Y_{t+k})}} \text{ or } P_k = \frac{\gamma_k}{\gamma_0} \tag{2}$$

Where $Var(Y_t) = Var(Y_{t+k}) = \gamma_0$, γ_k is called the autocovariance function. The autocorrelation function is used to identify the Moving Average (MA) model where the selection order for selecting the MA model is chosen from the lag in the ACF correlogram which falls at lag k. Meanwhile, Partial Autocorrelation Function (PACF) is the relationship between Y_t and Y_{t+k} by ignoring $Y_{t+k-1}, Y_{t+k-2}, \dots, Y_t$.

3. Differentencing is done if the time series data is not stationary in the mean and transforming is done if the time series data is not stationary in the variance. Differentencing is done up to d times until the time series data is stationary.
4. The parameters p, d and q in ARIMA are determined.
5. Some of the best ARIMA models are currently determined
6. Diagnostic Checking. After determining some of the best temporary ARIMA models, these models are tested for parameters whether they are significant or not, the residuals are correlated or not and the residuals are normally distributed or not.

The parameter significance test is carried out using the t-statistical test

Hypothesis

H0: The parameter is not significant

H1: Parameter is significant

Test Statistics (Harianto, 2018):

$$t = \frac{\hat{\theta}}{SE(\widehat{\theta})} \tag{3}$$

Decision: H0 is rejected if $|t| > t_{\frac{a}{2};df=n-np}$, np =number of parameters or p-value$< a$

The residuals correlation test is using Ljung-Box test. The use of the Ljung-Box test is to find out whether the autocorrelation of residuals meets the white-noise requirements. The following hypothesis is used (Sadik, 2015):

H0 : $\rho_1 = \rho_2 = \cdots = \rho_k = 0$ (ARIMA residual autocorrelation (p,d,q) is not significant or meets white-noise requirements)

H1 : $\rho_i \neq 0, i = 1, 2, 3, \dots, k$ (ARIMA residual autocorrelation (p,d,q) is significant or does not meet white-noise requirements)

The test statistic used is the Ljung-Box test:

$$Q^* = n(n+2)\sum_{k=1}^{k}\frac{\hat{r}^2_{\varepsilon(k)}}{n-k} \tag{4}$$

Rejection area: Reject H0 if $Q^* > X^2_{a;df=k-m}$ with k is the lag and m is the number of parameters estimated in the model ($m = p + q$) or p-value$< a$

The normality test is used to determine whether the error term approaches a normal distribution. A normality test is needed if the number of observations is less than 30. If the number of observations exceeds 30, then there is no need to carry out a normality test because the distribution is close to normal (Ajija et al, 2011).

7. The ARIMA model equation is determined. This determination can be determined by looking at the smallest MSE, MAPE and AIC to determine the coefficients. The criterion for the best model using MSE is to look for the lowest MSE value. In general, the MSE formula can be written as follows (Makridakis et al,1999):

$$MSE = \frac{\sum_{t=1}^{n}(Yt - Ft)^2}{n} \tag{5}$$

MAPE indicates how big the error in forecasting is compared to actual data. In general, MAPE can be formulated as follows:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}|PE_t| \tag{6}$$

Where n is the number of periods and PE_t is the percentage error:

$$PE_t = \left(\frac{Y_t - F_t}{Y_t}\right) \times 100\% \tag{7}$$

According to (Agustini et al, 2018) to assess the quality of a good model the Akaike information criterion or AIC can be used and is defined as follows:

$$AIC = -2logL(\hat{\theta}) + 2M \tag{8}$$

8. The forecast results with actual data are compared and the accuracy of a model is calculated to determine the accuracy of the model.
9. Forecasting. After the best model is determined, forecasting can be done for the Rupiah exchange rate against the US Dollar in the period January 20 2023 – January 31 2023.

RESULTS AND DISCUSSION

Observational data

A description of the selling rates for the period November 20 2020 to November 20 2022 is presented graphically in Figure 1.

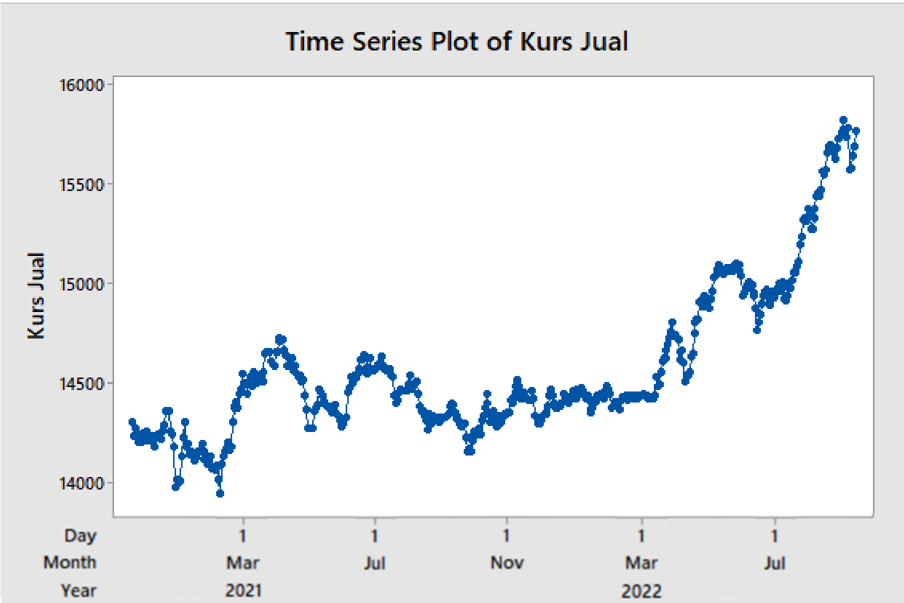

Figure 1. Data plot of selling rate of Rupiah against US Dollar 20 November 2020 - 20 November 2022

Based on Figure 1, it can be seen that the selling rate of the Rupiah against the US Dollar for the period November 20 2020 – November 20 2022 has an upward trend pattern and is experiencing erratic changes every day, this shows that the data is fluctuating. In the period 20 November 2020 – 20 November 2022 the highest selling rate is on 7 November 2022 at a price of Rp. 15,815 and the lowest selling rate is on February 16, 2021 at a price of Rp. 13,944. In the range of 20 November 2020 – 20 November 2022 the selling rate has an average value of Rp. 14,571.13.

Calculation Results

Identification of the ARIMA model

The first step in determining stationary data or cannot be known through the ACF and PACF diagrams of the data and can do the Augmented Dicky Fuller (ADF) test. ACF and PACF diagrams can be seen in Figure 2 and Figure 3. ADF test results can be seen in Table 1.

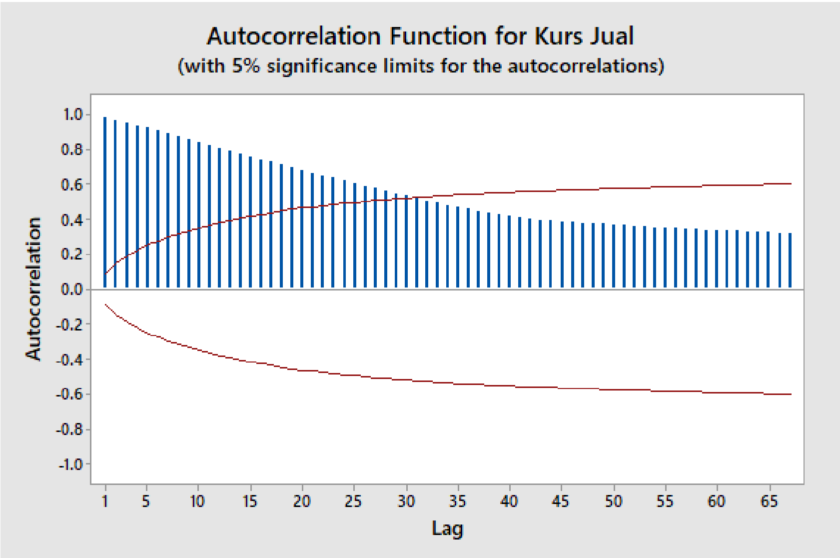

Figure 2. ACF diagram of selling rate data of the Rupiah against the US Dollar 20 November 2020-20 November 2022

Table 1. ADF test results data on selling exchange rate of the Rupiah against the US Dollar November 20, 2020 - November 20, 2022

Result	Statistik-t	P-Value	Decision
ADF	0,799455	0,9940	Accept H_0
1%	-3,443175		
5%	-2,867089		
10%	-2,569787		

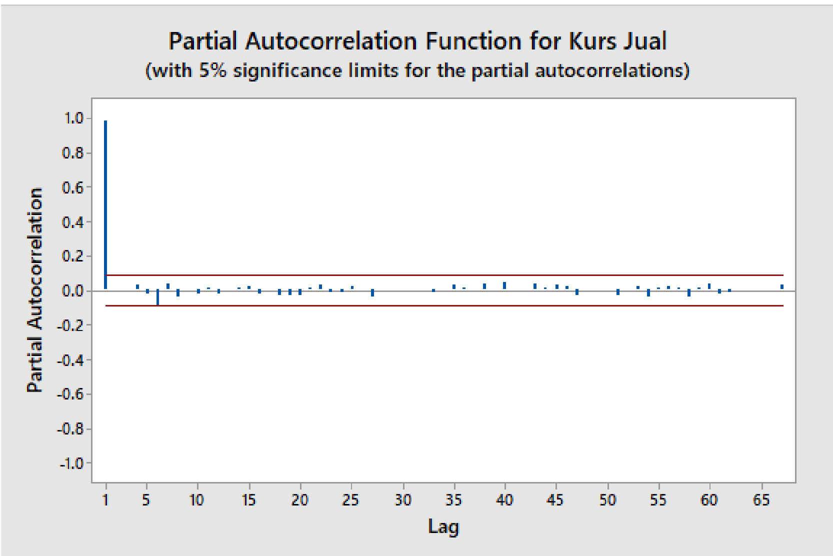

Figure 3. PACF Diagram of Selling Rate Data of the Rupiah against the US Dollar 20 November 2020-20 November 2022

Based on Figure 2 and Figure 3 it can be stated that the data is still not stationary because the first 3 lags come out of the significant boundary line and in Table 1 the ADF test results show p-value$>\alpha$ and the t-statistic value of 0,799455 is greater than the critical value of DF ($= -3{,}443175, -2{,}867089$, and $-2{,}569787$) then the conclusion that can be obtained is accept H0 which means the data is not stationary.

Stationary data

Because the data is not stationary, differencing is carried out until the data is stationary. The following is a plot of data that has been differencing, presented in Figure 4.

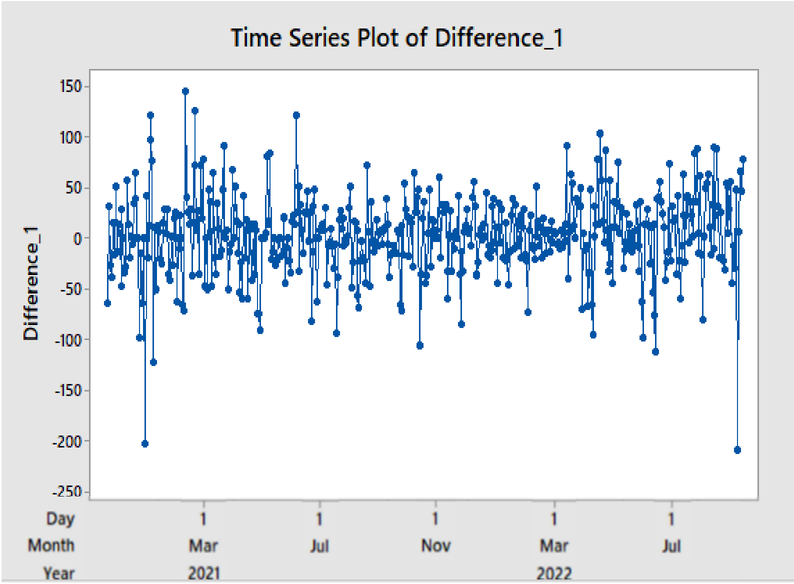

Figure 4. Data plot of selling rate of Rupiah against US Dollar for the period 20 November 2020-20 November 2022 first differencing

It can be seen in Figure 4 that the data is in the middle average. To ensure that the data is stationary at the first differencing, it can be seen in the ACF, PACF diagrams and the ADF test is carried out on the differencing data. The following are the differencing ACF and PACF diagrams presented in Figure 5 and Figure 6. The results of the ADF test on differencing data are presented in Table 2.

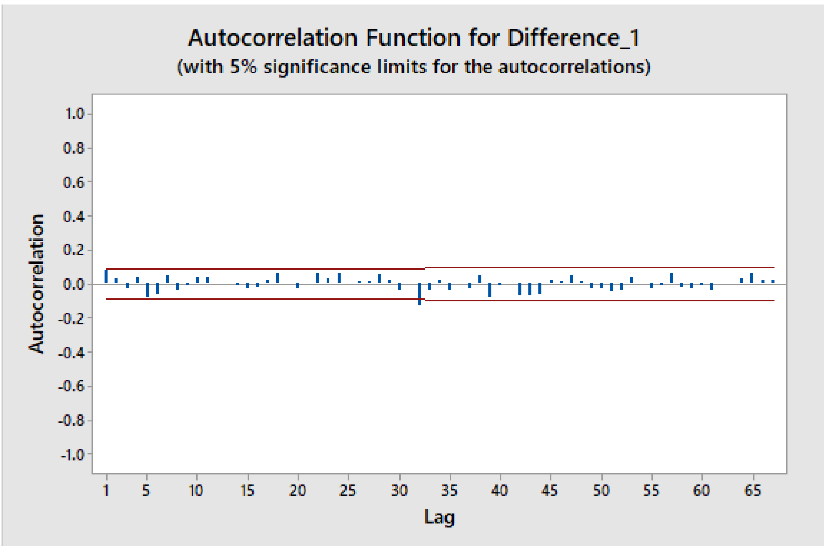

Figure 5. ACF diagram the first difference is the selling exchange rate data for the Rupiah against the US Dollar November 20, 2020 - November 20, 2022

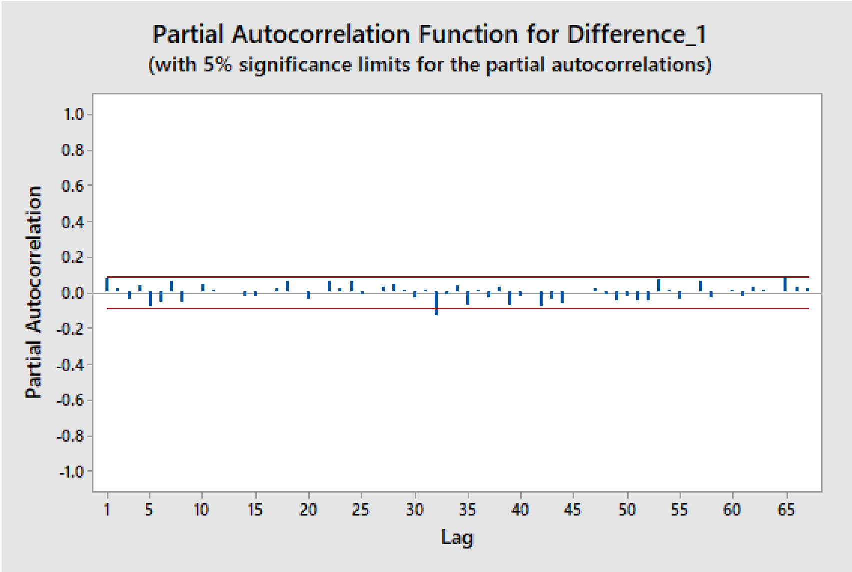

Figure 6. PACF diagram the first difference is the selling exchange rate data for the Rupiah against the US Dollar November 20, 2020 - November 20, 2022

Table 2. ADF test results data on the selling exchange rate of the Rupiah against the US Dollar November 20, 2020 - November 20, 2022 which has been differencing

Result	T-Statistic	P-Value	Decision
ADF	-20,50703	0,0000	Accept H_1
1%	-3,443202		
5%	-2,867101		
10%	-2,569793		

Figures 5 and 6 show that ACF and PACF do not have the first 3 lags that are outside the significant limit. In Table 2 the ADF test results show p-value$< a$ and the t-statistic value of -20.56897 is smaller than the critical DF value $(= -3.443202, -2.867101$ and $-2.569793)$ so the conclusion that can be obtained is reject H_0 that the selling rate data is stationary.

Determination of parameters p, d, and q

The ACF and PACF diagrams in Figures 5 and 6 show that there is no lag that goes beyond the significant limit until the 32nd lag, this indicates an AR and MA process. However, if the parameters p and q are too many then the model is less stable. It can be seen in the ACF and PACF diagrams that lag 1 and lag 5 are almost outside the significant line, so the estimation of a temporary model can be determined with a maximum of 5 p parameters and a maximum of 5 q parameters.

Determination of the temporary ARIMA model

The estimated results of the ARIMA model are shown in Table 3.

Table 3. ARIMA model conjecture

Model	ARIMA Model
I	(1,1,1)
II	(0,1,2)
III	(2,1,2)
IV	(2,1,3)
V	(4,1,4)

Table 3 shows the alleged ARIMA temporary models, including ARIMA (1,1,1), ARIMA (0,1,2), ARIMA (2,1,2), ARIMA (2,1,3) and ARIMA (4, 1.4), while the model equation can be seen in Table 4.

Table 4. Preliminary model parameter estimation

Model	Equation
ARIMA (1,1,1)	$Y_t = 2{,}222 + 1{,}2419Y_{t-1} - 0{,}2419Y_{t-2} - 0{,}1581\varepsilon_{t-1} + \varepsilon_t$
ARIMA (0,1,2)	$Y_t = 2{,}931 + Y_{t-1} + 0{,}0844\varepsilon_{t-1} + 0{,}0335\varepsilon_{t-2} + \varepsilon_t$
ARIMA (2,1,2)	$Y_t = 8{,}196 + 0{,}0356Y_{t-1} + 0{,}1454Y_{t-2} + 0{,}8190Y_{t-3} + \varepsilon_t - 1{,}0475\varepsilon_{t-1} - 0{,}8965\varepsilon_{t-2}$
ARIMA (2,1,3)	$Y_t = 1{,}0896 + 1{,}1813Y_{t-1} + 0{,}2658Y_{t-2} - 0{,}4471Y_{t-3} + 0{,}0941\varepsilon_{t-1} + 0{,}4283\varepsilon_{t-2} + 0{,}1028\varepsilon_{t-3} + \varepsilon_t$
ARIMA (4,1,4)	$Y_t = 3{,}385 + 1{,}6221Y_{t-1} - 0{,}8976Y_{t-2} + 0{,}5669Y_{t-3} - 1{,}0766Y_{t-4} + 0{,}7852Y_{t-5} + 0{,}5382\varepsilon_{t-1} - 0{,}2152\varepsilon_{t-2} + 0{,}3232\varepsilon_{t-3} - 0{,}8555\varepsilon_{t-4} + \varepsilon_t$

Model diagnostics

Parameter significance test

The parameter significance test was carried out on the predicted model in Table 3. In testing these parameters, the following hypotheses were used:
H0 : Parameter is not significant
H1 : Significant parameter
With test statistics:

$$t = \frac{\hat{\theta}}{SE(\widehat{\theta})}$$

With a level of $\alpha = 5\%$, the rejection area for H_0 is $|t| > t_{(a/_2;df=n-np)}$ or $p - value\ <\ 0{,}05$.
After carrying out the significance test, it can be stated that models with significant parameters are ARIMA (2,1,2) and ARIMA (4,1,4) models. While the other alleged models are not significant.

Model fit test

The model fit test consists of a white noise residual assumption test and a normal distribution residual assumption test. Because the observations are more than 30, it is not necessary to test the assumption of normal distribution of residuals. This residual assumption test was carried out on models with significant parameters, namely the ARIMA (2,1,2) and ARIMA (4,1,4) models.
The residual white-noise test is carried out using the Ljung-Box test statistic with the hypothesis:
H0 : the residue is white-noise
H1 : the residue is not white-noise

Table 5. White-noise residual test results

Model	Lag	P-Value	Decision
ARIMA (2,1,2)	12	0,647	Accept H_0
	24	0,872	
	36	0,708	
	48	0,638	
ARIMA (4,1,4)	12	0,287	Accept H_0
	24	0,606	
	36	0,504	
	48	0,540	

Based on Table 5 it can be seen that the ARIMA (2,1,2) and ARIMA (4,1,4) models have a $p-value > 0.05$. This shows that ARIMA (2,1,2) and ARIMA (4,1,4) fulfill the white-noise assumption.

Calculation of MAPE, MSE, and AIC

The results of MAPE, MSE, and AIC calculations are presented in Table 6.

Table 6. Calculation results of MAPE, MSE, and AIC

Model	MAPE	MSE	AIC
ARIMA [2,1,2]	1,2458%	71.946,5996	10,23316
ARIMA [4,1,4]	1,2491%	72.358,7644	10,22675

Based on the calculation results of MSE, MAPE, AIC from the ARIMA(2,1,2) and ARIMA (4,1,4) models it can be concluded that ARIMA(2,1,2) is the best model for forecasting because it has MSE and MAPE values smallest

Forecasting

ARIMA forecasting results using ARIMA (2,1,2) are presented in Table 7.

Table 7. Forecasting results of ARIMA (2,1,2)

Period	Forecast Result (Rp.)
20/1/2023	15.901,9
23/1/2023	15.905,0
24/1/2023	15.910,7
25/1/2023	15.918,1
26/1/2023	15.925,2
27/1/2023	15.930,2
30/1/2023	15.932,4
31/1/2023	15.932,0

As seen in Table 7, the forecasting results using ARIMA (2,1,2) produce the highest selling exchange rate in the period January 30, 2023 of Rp. 15,932.4 and the smallest in the period January 20 2023 is Rp. 15,901.9 and an average of Rp. 15,919.4

CONCLUSION

Based on the results obtained in this study, it can be concluded that:

(i) Data on the selling rate of the Indonesian Rupiah against the US Dollar for the period November 20 2020 – November 20 2022 has the characteristics of being fluctuating, not stationary with respect to the variety and the median average. This makes data on the selling rate of the Indonesian Rupiah against the US Dollar for the period November 20 2020 – November 20 2022 predictable using the ARIMA model.

(ii) The best ARIMA model for predicting data on the selling rate of the Indonesian Rupiah against the US Dollar for the period November 20 2020 – November 20 2022 is the ARIMA model (2,1,2) with an MSE value of 71,946.5996, a MAPE of 1.2458% and AIC of 10.23316. The ARIMA model (2,1,2) obtained is as follows:

$$Y_t = 8{,}196 + 0{,}0356Y_{t-1} + 0{,}1454Y_{t-2} + 0{,}8190Y_{t-3} + \varepsilon_t - 1{,}0475\varepsilon_{t-1} - 0{,}8965\varepsilon_{t-2}$$

From the ARIMA model (2,1,2) the highest selling exchange rate was obtained in the January 30 2023 period of Rp. 15,932.4 and the smallest in the period January 20 2023 is Rp. 15,901.9 and an average of Rp. 15,919.4

Time series data modeling is developing rapidly, including modeling using more modern machine learning methods and statistical inference. Therefore, for further research, statistical inference and the use of machine learning techniques are highly recommended. This is very possible because time series data has a long data sequence, making it possible to obtain accurate machine learning modeling results.

AUTHOR CONTRIBUTIONS

Each author of this article played an important role in the process of method conceptualization, simulation, and article writing.

CONFLICT OF INTEREST

The authors declare that they have no conflicts of interest.

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