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Forecasting the Saudi Riyal to Indonesian Rupiah Exchange Rate Using ARIMA

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Abstract. A Currency exchange rate is an essential indicator in a country's economy. The exchange rate of a country's currency constantly fluctuates against another country's currency at any time, such as the riyal exchange rate against the rupiah. There are several methods to determine the movement of the currency exchange rate and to forecast time series data, such as Autoregressive Integrated Moving Average (ARIMA). ARIMA is a time series data forecasting method that can handle data that is not stationary to the mean and variance, such as the riyal exchange rate against the rupiah, which fluctuates irregularly. This study will forecast the riyal exchange rate against the rupiah at Bank Indonesia. The data used is daily data. The R Studio program studies the minimum AIC value to select the best model. The ARIMA (2,1,0) model is the best in forecasting the Saudi Arabian Riyal exchange rate (SAR) against the Indonesian rupiah (IDR) with an estimated forecast error of 0.26%.

Keywords: ARIMA, Currency, Exchange Rate, Forecasting, Time Series

1 Introduction

The global market economy plays an essential role as a platform for transactions between countries in the implementation of global trade in commodities or services. Money can be used as legal tender in international exchange to procure or sell goods or services. Transactions involving foreign currencies are increasing due to an increasingly integrated global economy. The international monetary structure necessitates the synchronized conversion of countries' currencies or the use of a universal currency. Currency exchange rates have far-reaching implications in both domestic and international economic contexts, resulting in the involvement of almost every country around the world in global affairs [1]. One of the most critical indicators in economics is currency valuation. The value of a country's currency often fluctuates about the currencies of other countries. Currency fluctuation is the rise and fall of a currency's price against other currencies. Many factors contribute to fluctuations, including supply and demand for foreign currency, the concept of balance of payments (BoP), inflation rates, interest rates, income levels, government surveillance, public expectations, and speculation. The exchange rate is the price of a country's currency when measured and expressed in the currency of another country [2].

Indonesian pilgrims performing Hajj and Umrah in the holy land of Makkah require the utilisation of Saudi Arabia's national currency to conduct necessary transactions during their stay within the borders of Saudi Arabia. Although the rupiah can still be used to make transactions in Saudi Arabia, the riyal is the main currency used in Saudi Arabia. Therefore, Indonesian pilgrims need to have the official currency of Saudi Arabia, which is the Saudi Arabian Riyal (SAR)[3]. Countries around the world are involved in the practice of international diplomacy. One of them is the international relations that exist between Indonesia and Saudi Arabia. The international relations are in the economy, education, and security. One of the factors that led to an increase in the economy in Saudi Arabia was Indonesia's contribution to sending its population to the holy land of Makkah to perform Hajj and Umrah. This is supported by Indonesia having the largest Muslim population in the world [4].

The determination of future currency prices can be achieved by using forecasting techniques. Forecasting techniques aim to anticipate future events by analysing past data and systematically using scientific methodology, and the forecasting results are expected to be close to the actual situation. According to [5], forecasting is the process of accurately predicting future events while considering all available information, such as historical data and knowledge relating to future events that may affect the forecasting process. The study of forecasting includes quantitative approaches, which can be further categorized into time series methods and correlation methods [5].

Modelling time series data usually uses classical models, including the Autoregressive (AR) model. This model is linear in time series that can generally be applied to most statistical and economic data, such as currency exchange rate data. The data fluctuates around a value at any given time. The fluctuating condition of the data on currency exchange rates indicates a change in structure, where different conditions change at certain times [6]. Auto Regressive Integrated Moving Average (ARIMA) explains the time series under consideration based on its previous values: its lags and the lagged prediction errors. It can be helpful in the future forecast for a nonstationary time series exhibiting patterns and is not irregular white noise. The 3 characteristic terms of the ARIMA model are the parameters (p, d, q), wherein each of the terms is the order of the AR term, the differencing needed to change the time series into a stationary one, and the MA term, respectively. The term AR in ARIMA signifies a linear regression model that uses its lags to predict. Linear regression models give the finest results when there is no correlation between the predictors and they are not dependent on each other. A time series whose properties do not change over time is called stationary [7].

Methods that can be used for smoothing time series data analysis are AR (Autoregressive), MA (Moving Average), ARMA (Autoregressive Moving Average), and ARIMA (Autoregressive Integrated Moving Average) models. ARIMA is a time series forecasting method that can handle data that is not stationary in mean and variance. The ARIMA method aims to produce accurate short-term forecasting and find the time pattern used in forecasting. The ARIMA method consists of AR (Autoregressive), MA (Moving Average) methods, as well as stationary processes in the data [8].

Many cases can be applied to ARIMA models. Among them are stock prices [9], South Kalimantan growth[10], extreme weather[11], and poverty rates[12]. While the South Kalimantan growth case has several findings, the Covid-19 pandemic intervention significantly affects economic growth in South Kalimantan, which is reflected in the significance of all parameters in the model used. Second, the intervention model used has an MAPE of 11.24 per cent, which has good accuracy. Third, annual economic growth in South Kalimantan in 2023 and 2024 is predicted to be 4.9 per cent. This research will examine forecasting the riyal exchange rate to the rupiah with ARIMA. Further analyzed the performance of the model in predicting the future.

2 The Comprehensive Theoretical Basis

2.1 Time Series

A time series is a set of observations x_t, where each observation is recorded within a specific time t. Time series are divided into two types, namely discrete and continuous. A discrete time series is one in which the observations at times are a discrete set. A constant time series is obtained when observations are made continuously in a specific time interval. Continuously in a particular interval of time, suppose to = [0,1] [8].

2.2 Data Stationarity

ARIMA is widely used as a method for forecasting, one of which is in the economic field. Many the data in economics is integrated or non-stationary. The stationary to prepare data is prepared for statistical modeling, and the time series are transformed to stationarity by taking the natural log, the difference, or residuals from regression. The Augmented Dickey-Fuller test, or ADF test, is used to test the stationarity of the data used in this article. Here is the Augmented Dickey-Fuller (ADF) equation[13]:

$$\nabla X_t = \mu + \delta X_{t-1} + \sum_{i=1}^{k} \phi_i \nabla X_{t-i} + \varepsilon_t \tag{1}$$

The Dickey-Fuller (DF) test statistic is as follows:

$$\text{ADF} = \frac{\hat{\delta}}{SE(\hat{\delta})} \tag{2}$$

Where $SE(\hat{\delta})$ is the standard error for $\hat{\delta}$ the hypothesis used in this test is as follows:

$H_0: \delta = 0$ (non stasionery)

$H_1: \delta \neq 0$ (stasionery)

2.3 Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF)

Autocorrelation is a condition in which the residuals of an observation are correlated with the residuals of other observations. In time series analysis, to identify the order of the time series model, ACF and PACF are used. The autocorrelation function for a sample can be calculated with the following equation [14]:

$$\hat{\rho}_k = \frac{\hat{\gamma}_k}{\hat{\gamma}_0} = \frac{\sum_{t=1}^{n-k}(X_t - \bar{X})(X_{t+k} - \bar{X})}{\sum_{t=1}^{n}(X_t - \bar{X})^2} \tag{3}$$

Partial autocorrelation function (PACF) is the correlation between (X_t) and (X_{t+k}) after the variable $X_{t+1}, X_{t+2}, \dots, X_{t+k}$are removed. The partial autocorrelation function of the sample can be calculated with the following mathematical equation:

$$\boldsymbol{\phi_{k+1,k+1} = \frac{\rho_{k+1} - \sum_{j=1}^{k-1} \phi_{kj}\rho_{k+1-j}}{1 - \sum_{j=1}^{k-1} \phi_k \rho_j}} \tag{4}$$

2.4 ARIMA Model Identification

Autoregressive (AR(p))

Autoregressive (AR) models show how current values (X_t) and previous values (X_{t-1}) relate to each other, as well as the effect of residual values (ε_t). The systematic form of p-degree autoregressive is as follows [15]:

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_p X_{t-p} + \varepsilon_t \tag{5}$$

Moving Average (MA(q))

The Moving Average (MA) model shows how current values (X_t) and past residual values (ε_{t-q}). relate to each other.The Moving Average model of order q has the following equation[15]:

$$X_t = \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \tag{6}$$

Autoregressive Integrated Moving Average (ARIMA (p, d, q))

The ARMA assumes that the process is stationary. It means that the time series has at least a constant mean and variance, and its covariance function depends only on the time difference. When non-stationarity is observed, data transformations are needed. Considering non-stationarity in variance, the logarithm transformation is the most popular solution, whereas non-stationarity in mean is commonly removed by differencing [16]. Several techniques are available to search for the best orders of the ARIMA model. The AR method performs a grid search through all combinations of parameters at a given interval and selects a model with the minimum Akaike Information Criterion (AIC) value. Before applying Auto ARIMA to our model, a seasonal decomposition was conducted to test for seasonality behaviours in the dataset [17].

The data will be formed into a linear equation and error terms in this ARIMA model. This ARIMA (p, d, q) model has orders p, d, and q are, respectively, the order of the AR model, the order of integration or differencing count, and the order of the MA model. MA model. Mathematically, the ARIMA (p, d, q) model can be written as follows [14]:

$$\phi_p(B)(1 - B)^d X_t = \theta_q(B)\varepsilon_t \tag{7}$$

2.5 Diagnostic Checking

In the best model, the residuals obtained are expected to have white noise properties, following a normal, independent, and identical distribution. Therefore, model validation and diagnostic tests involve analyzing the residuals to test for white noise characteristics noise characteristics [18]. A more appropriate technique to establish the independence of the residuals is to examine the Ljung-Box Q-test statistic. This assumption can be tested with Ljung-Box, which hypothesizes as follows [14]:

$H_0 : \rho_1 = \rho_2 = \cdots = \rho_k = 0$ (white noise)

$H_1 : \rho_k \neq 0$ (not white noise)

Test Statistic:

$$LB = n(n+2)\sum_{k=1}^{j}\frac{\hat{\rho}_k^2}{(n-k)}, n > j \tag{8}$$

2.6 Akaike Information Criteria (AIC)

The method used to look at the best model selection criteria is the AIC. AIC is a requirement used to select the best model [19]. This criterion observes the number of parameters in the model. The AIC equation in model selection is as follows [8]:

$$AIC = n\,ln\left(\frac{SSE}{n}\right) + 2f + n + n\ln(2\pi) \tag{9}$$

2.7 Mean Absolute Percentage Error (MAPE)

Error calculation serves as a means to assess the accuracy of the model that has been obtained. This evaluation compares the forecast data produced by the model and the actual data. Forecasting techniques that make the lowest error are considered the most effective. the MAPE method is used to determine the amount of deviation that occurs between forecast data and actual data. MAPE is the average percentage error (difference) between actual data and forecast results. Here's the formula for calculating MAPE [20]:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|X(t) - F(t)|}{X(t)} \times 100\% \tag{10}$$

3 Method

The type of research conducted is quantitative research. Research with a quantitative analysis approach and emphasis on numerical data (numbers) is then analyzed using appropriate statistical methods. The approach used is ARIMA. To facilitate the research, researchers use the help of R Studio software. The data used is secondary data. The data was obtained from the website www.bi.go.id, which comes from Bank Indonesia. This study utilizes daily data on the SAR/IDR exchange rate from July 11, 2022, to November 30, 2023.

4 Results and Discussion

The first step is to plot the data, the purpose of plotting the data is to see if the data is stationary on the mean and variance. If the data is not stationary with respect to variance, it needs to be transformed and if the data is not stationary with respect to the mean, it needs to be differenced. Here is a data plot of the riyal exchange rate against the rupiah:

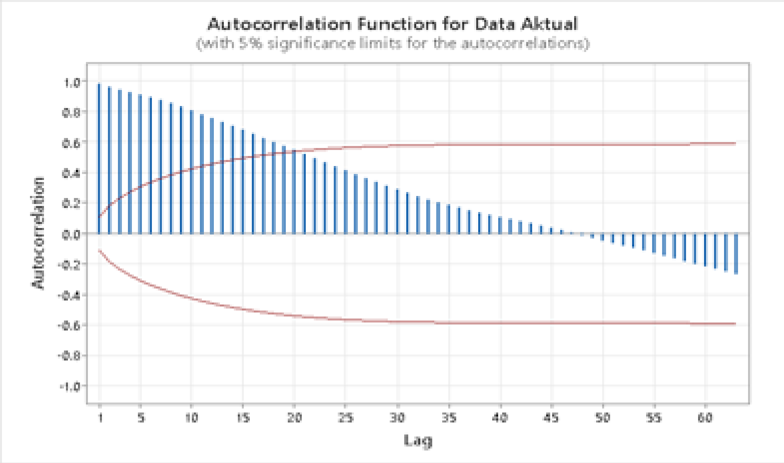

Fig 1. ACF Plot of Riyal to Rupiah Exchange Rate Data

The ACF plot in Figure 1 exceeds the significance limit, so it can be said that the data is not yet stationary in terms of mean and variance. However, to check that the data is not stationary, it is necessary to conduct the Augmented Dickey-Fuller (ADF) test at a significant level of α=0.05. Statistically, the ADF test value is obtained with a p-value of 0,7269, which means that the $p - value > 0{,}05$, so it can be said that the data is not yet stationary on the mean and variance. The next thing to do is transform the data. Before transforming the data, first determine the lambda value (rounded value) using a Box-Cox plot.

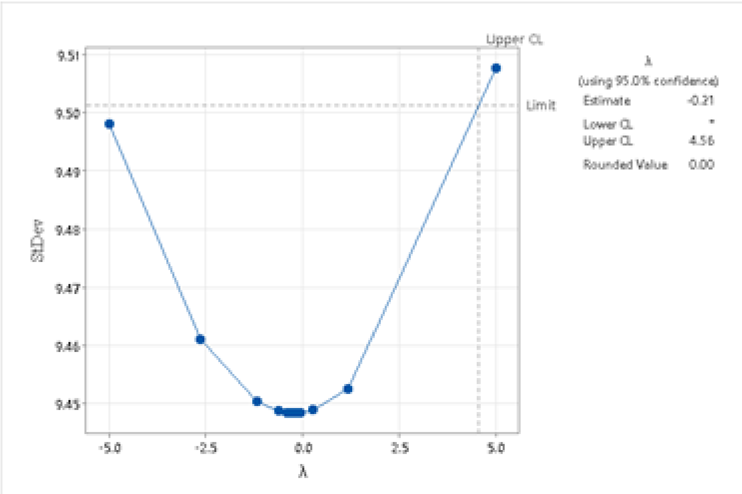

Fig 2. Box-Cox Test Plot Before Transformation

The rounded value (λ) obtained is 0,00, based on the lambda value (λ) obtained, the data can be said to be not stationary on variance so that the type of transformation performed is ln (X_t). The following is the result of the time series data transformation plot:

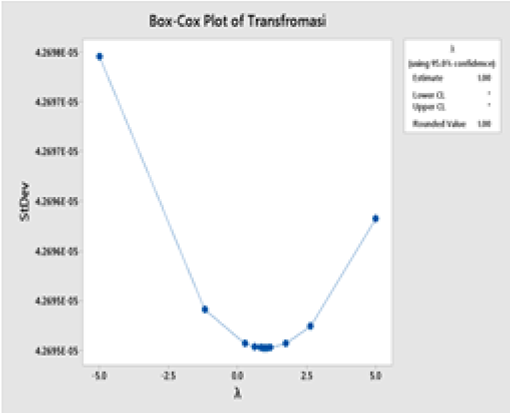

Fig 3. Box-Cox Test Plot After Transformation

After transforming, the rounded value (λ) is 1,00, so the data is stationary for variance.

Furthermore, first-order differencing is performed because the data is not yet stationary to the mean. The following is a data plot after transforming and first-order differencing.

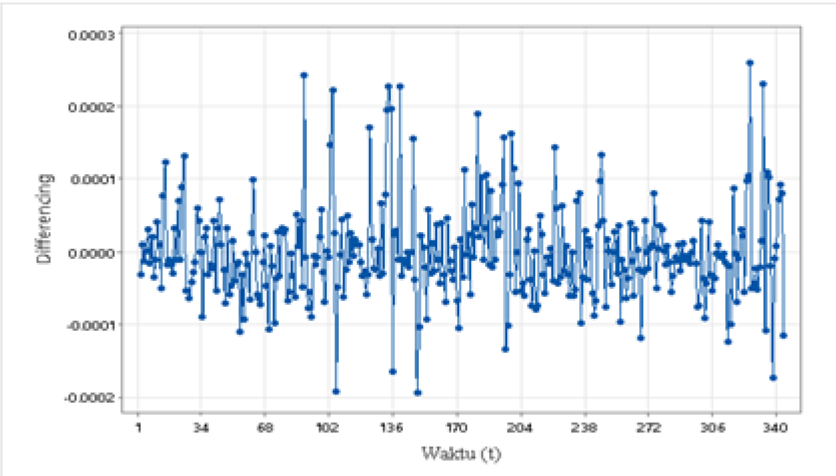

Fig 4. Box-Cox Test Plot After Transformation and Differencing

After transformation and differencing, the data plot shows that the data has increased and decreased around the mean. The ADF test can strengthen this after performing the transformation and differencing process with a $p-value\ =\ 0{,}01$, because the $p-value\ <0{,}05$It can be concluded that the data have stationary properties. The next step after stationary data is the identification of the ARIMA model.

4.1 Identification of Model ARIMA

The ARIMA model is identified by making ACF and plots. ACF and PACF plots can be seen after the transformation and differencing process:

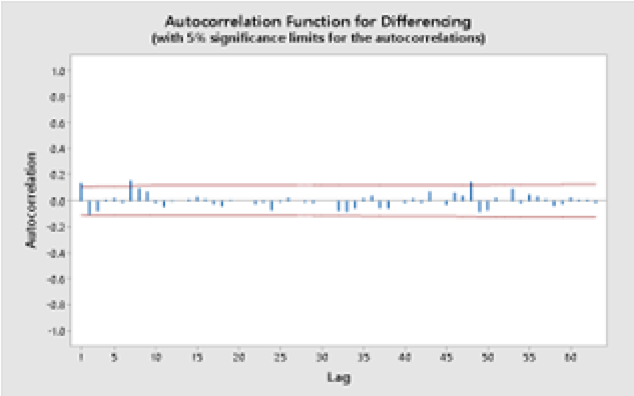

Fig 5. ACF Plot After Transformation and Differencing

In the ACF plot, there is a cut at lag 1, so it is suspected that there is MA (1).

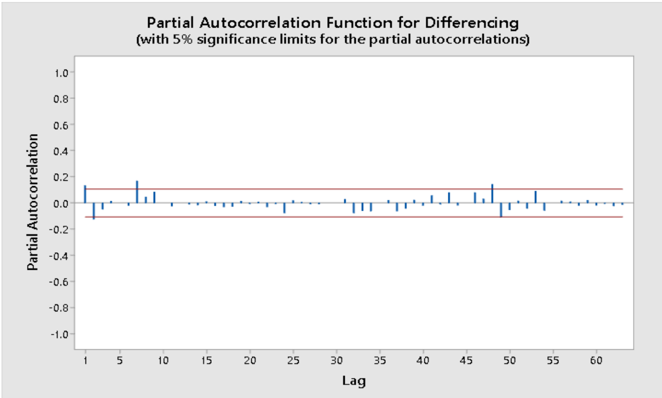

Fig 6. PACF Plot After Transformation and Differencing

The PACF plot gradually drops to zero at the 2nd lag so it is suspected to be AR (2). Then the possible ARIMA (p, d, q) models with differencing once are ARIMA (0,1,1), ARIMA (1,1,0), ARIMA (1,1,1), ARIMA (2,1,0), and ARIMA (2,1,1). After obtaining the possible ARIMA models, the next step is to estimate the parameters of each model.

The step after obtaining the model from the ACF and PACF graphs is to estimate the model parameters and test the significance of the model parameters. The following are the results of estimating the model parameters and testing the significance of the model parameters:

Table 1. Parameter Test Estimation

Temporary Model	Parameter Estimation	Estimated Value	Standard *Error*	$p-value$	Decision
ARIMA (0,1,1)	$\hat{\theta}_1$	-0.1675	0.0537	0.002	Significant
ARIMA (1,1,0)	$\hat{\phi}_1$	0.1364	0.0539	0.012	Significant
ARIMA (1,1,1)	$\hat{\phi}_1$	-0.245	0.299	0.414	Not Significant
	$\hat{\theta}_1$	-0.404	0.283	0.154	Not Significant
ARIMA (2,1,0)	$\hat{\phi}_1$	0.1540	0.0541	0.005	Significant
	$\hat{\phi}_2$	-0.1234	0.0542	0.024	Significant
ARIMA (2,1,1)	$\hat{\phi}_1$	0.428	0.381	0.262	Not Significant
	$\hat{\phi}_2$	-0.1638	0.0659	0.013	Significant
	$\hat{\theta}_1$	0.278	0.385	0.471	Not Significant

The parameter estimation table shows that the ARIMA (0,1,1), ARIMA (1,1,0), and ARIMA (2,1,0) models are significant, this is because the p-value <0.05. While ARIMA (1,1,1), ARIMA (2,1,1) proved insignificant because the $p - value > 0.05$.

4.2 Diagnostic Checking

This stage aims to check whether the model used fulfills the assumption of white noise characteristic assumptions required in the ARIMA model. The required characteristic is no autocorrelation between residuals, which will be tested using the Ljung-Box test. The second property is that the residuals follow a normal distribution. The following is the white noise test table:

Table 2. White Noise Test

Model	$p - value$	Decision
ARIMA (0,1,1)	0.8208	*White noise*
ARIMA (1,1,0)	0.7557	*White noise*
ARIMA (2,1,0)	0.9070	*White noise*

Ljung-Box test output for ARIMA (0,1,1), ARIMA (1,1,0), and ARIMA (2,1,0) models, proved to have met the assumptions, because the $p - value > 0{,}05$.

Next, the residual normality test aims to see the normality of the residuals. The model is said to be good if the residuals are normally distributed. The following QQ plot of the residuals of the model:

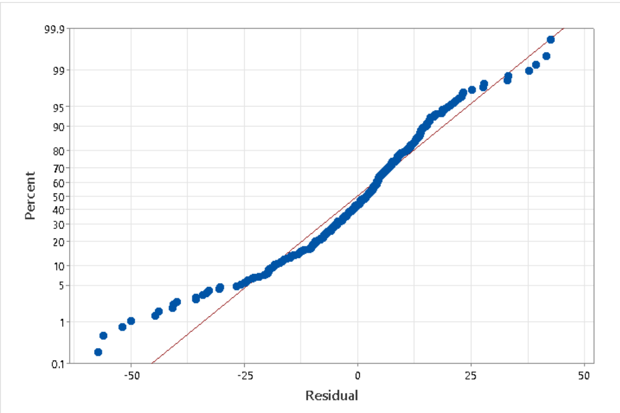

Fig 7. QQ Plot Model ARIMA (0,1,1)

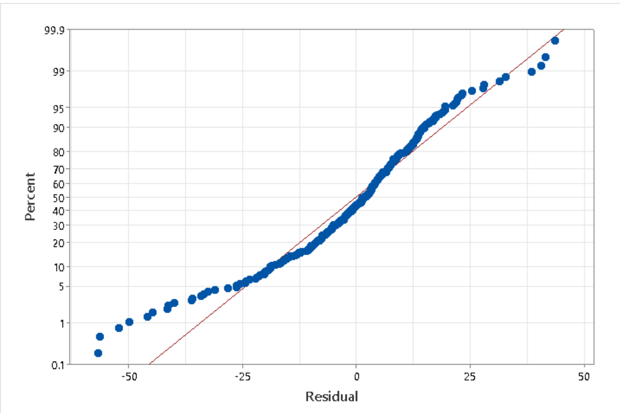

Fig 8. QQ Plot Model ARIMA (1,1,0)

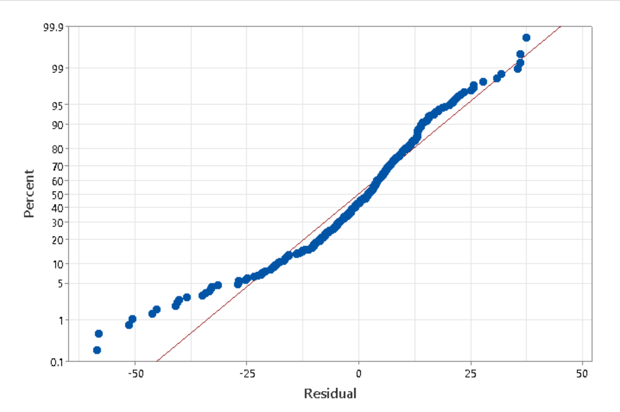

Fig 9. QQ Plot Model ARIMA (2,1,0)

The QQ plots of the ARIMA (0,1,1), ARIMA (1,1,0), and ARIMA (2,1,0) models show their residuals around the regression line.

4.3 Best Model Selection

The next step is to select the best model after testing each model's residual assumptions and the white noise process. The residual assumption test shows that the ARIMA (0,1,1), ARIMA (1,1,0), and ARIMA (2,1,0) models meet the white noise criteria.

Table 3. White Noise Test

Model	AIC
ARIMA (0,1,1)	2822.02
ARIMA (1,1,0)	2821.61
ARIMA (2,1,0)	2818.51

The AIC results show that ARIMA (2,1,0) has the lowest AIC value compared to ARIMA (0,1,1) and ARIMA (1,1,0). Thus, the ARIMA (2,1,0) model best analyzes the riyal exchange rate data against the rupiah. Systematically, the model can be written as follows:

$$\phi_2(B)(1-B)^1 X_t = \theta_0(B)\varepsilon_t$$

Or it can be written as follows:

$$X_t = (\phi_1 + 1)X_{t-1} - (\phi_1 - \phi_2)X_{t-2} - \phi_2 X_{t-3}$$

If all parameter estimation values are included, the model will become:

$$X_t = (1{,}1540)X_{t-1} - (0{,}2774)X_{t-2} + (0{,}1234)X_{t-3}$$

4.4 Mean Absolute Percentage Error (MAPE)

After analyzing the data, the last step is to measure the accuracy of the data analysis results. MAPE is required to obtain an estimate of the prediction error. The Mape value of the ARIMA Model (2,1,0) is obtained at 0,26%, which means that the accuracy of the ARIMA model can be said to be relatively high, when viewed from the resulting MAPE value of less than 10%, which means that based on the MAPE criteria, the forecasting results are excellent.

4.5 Forecasting the SAR/IDR Exchange Rate Using the ARIMA Model

The final stage in the time series data analysis is forecasting the riyal exchange rate data against the rupiah in the next period. ARIMA (2,1,0) was chosen as the best model to analyze the riyal exchange rate data against the rupiah. The following is the ARIMA (2,1,0) forecasting value:

Table 4. ARIMA Forecasting

t	Date	Actual Data	ARIMA Forecasting	Error ARIMA
345	1/12/2023	4138.46	4133.699	−4.761
346	4/12/2023	4117.62	4131.382	13.762
347	5/12/2023	4133.52	4130.252	−3.268
348	6/12/2023	4133.63	4130.371	−3.259
349	7/12/2023	4142.16	4130.532	−11.789
350	8/12/2023	4132.51	4130.541	−1.969
351	11/12/2023	4162.96	4130.522	−32.438

Based on the table of the results of forecasting the exchange rate of the riyal SAR against the rupiah IDR using ARIMA, a comparison graph can be seen that illustrates the actual data and forecasting results, as follows:

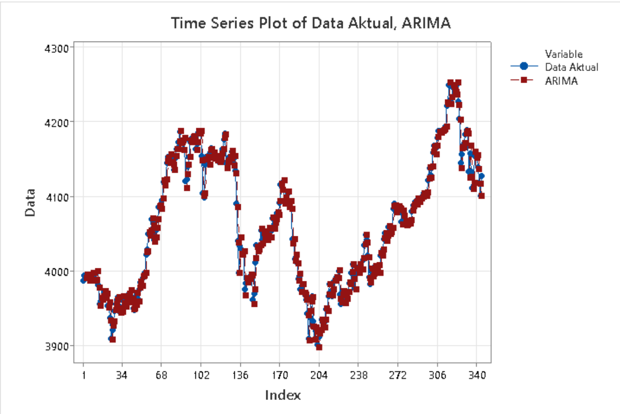

Fig 10. Comparison Plot of Actual Data and ARIMA Forecasting

The graph above shows that the ARIMA (2,1,0) forecasting data pattern is close to the actual data pattern, which means that the difference (error) generated by the forecasting data with the actual data is not too significant. So, it can be said that forecasting using ARIMA provides satisfactory results.

5 Conclusion

Based on the steps of the data analysis process carried out previously, it can be concluded that the best ARIMA model used in forecasting analysis of the riyal (SAR) exchange rate against the rupiah (IDR) is ARIMA (2,1,0). The MAPE value obtained on the ARIMA model is 0.26%.

References

[1] I. A. Fitri and D. Permana, "Matriks Peluang Transisi Fuzzy Time Series Markov Chain untuk Peramalan Kurs Riyal dengan Rupiah," vol. 2, no. 3, pp. 20–26, 2019.

[2] N. Yanti Gultom, Sudarno, and T. Wuryandari, "Prediksi Nilai Kurs Dollar Amerika Menggunakan Exponential Smoothing dengan Kajian Grafik Moving Average (EWMA) (Studi Kasus: Kurs Jual dan Kurs Beli Dollar Amerika)," *J. Gaussian*, vol. 4, no. 4, pp. 957–966, 2015, [Online]. Available: http://ejournal-s1.undip.ac.id/index.php/gaussian

[3] A. Wahyudi, W. Setiawan, Y. Dwi, and P. Negara, "PREDIKSI KURS MATA UANG RIYAL KE RUPIAH MENGGUNAKAN METODE SUPPORT VECTOR REGRESSION (SVR)," vol. 10, no. 2, 2024.

[4] F. Syarifudin, *Konsep, Dinamika dan Respon Kebijakan Nilai Tukar Di Indonesia*, Seri Keban., no. 24. 2015.

[5] R. J. Hyndman and G. Athanasopoulos, *Forecasting Principles And Practice*, Second. 2018.

[6] S. Yurinanda and D. M. Putri, "Pemodelan Laju Perubahan Nilai Tukar Rupiah (IDR) terhadap Dolar Amerika (USD) dengan Metode Markov Switching Autoregressive (MSAR)," vol. 14, no. 2013, pp.

54–65, 2021.

[7] U. M. Sirisha, M. C. Belavagi, and G. Attigeri, “Profit Prediction Using ARIMA , SARIMA and LSTM Models in Time Series Forecasting : A Comparison,” *IEEE Access*, vol. 10, no. December, pp. 124715–124727, 2022, doi: 10.1109/ACCESS.2022.3224938.

[8] P. J. Brockwell and R. A. Davis, *Introduction to Time Series and Forecasting*, Third. 2016. [Online]. Available: http://www.springer.com/series/417

[9] P. Harga, S. Pt, B. Mandiri, P. Tbk, and M. Metode, “Jurnal Paradigma Multidisipliner (JPM),” vol. 2, no. 2, pp. 111–118, 2021.

[10] A. Murjani, “Pemodelan pertumbuhan kalimantan selatan menggunakan arima intervensi,” vol. 07, no. 01, pp. 13–22, 2023.

[11] J. Journal and O. F. Mathematics, “Peramalan Data Cuaca Ekstrim Indonesia Menggunakan Model ARIMA dan Recurrent Neural Network,” vol. 5, no. 1, pp. 230–242, 2023.

[12] S. Sarbaini, Z. Zukrianto, and N. Nazaruddin, “Pengaruh Tingkat Kemiskinan Terhadap Pembangunan Rumah Layak Huni Di Provinsi Riau Menggunakan Metode Analisis Regresi Sederhana,” *J. Teknol. dan Manaj. Ind. Terap.*, vol. 1, no. 3, pp. 131–136, 2022, doi: 10.55826/tmit.v1iiii.46.

[13] D. M. Putri and Aghsilni, “Estimasi Model Terbaik Untuk Peramalan Harga Saham PT. Polychem Indonesia Tbk Dengan Arima,” *MAp J.*, vol. 1, no. 1, pp. 1–12, 2019.

[14] We. W. W. S, *Time Series Analysis: Univariate and Multivariate Methods*, Second., vol. 33, no. 1. 2006. doi: 10.1080/00401706.1991.10484777.

[15] C. Beneditto, A. Satrio, W. Darmawan, B. U. Nadia, and N. Hanafiah, “Time series analysis and forecasting of coronavirus disease in Indonesia using ARIMA model and PROPHET,” *Procedia Comput. Sci.*, vol. 179, no. 2020, pp. 524–532, 2021, doi: 10.1016/j.procs.2021.01.036.

[16] E. Chodakowska, “ARIMA Models in Electrical Load Forecasting and Their Robustness to Noise,” 2021.

[17] E. Dave, A. Leonardo, M. Jeanice, and N. Hanafiah, “ScienceDirect Forecasting Indonesia Exports using a Hybrid Model ARIMA- LSTM,” *Procedia Comput. Sci.*, vol. 179, no. 2020, pp. 480–487, 2021, doi: 10.1016/j.procs.2021.01.031.

[18] S. P. Fauzani and D. Rahmi, “Penerapan Metode ARIMA Dalam Peramalan Harga Produksi Karet di Provinsi Riau,” vol. 2, no. 4, pp. 269–277, 2023.

[19] A. Shadab, S. Ahmad, and S. Said, “Spatial Forecasting of Solar Radiation using ARIMA Model,” *Remote Sens. Appl. Soc. Environ.*, p. 100427, 2020, doi: 10.1016/j.rsase.2020.100427.

[20] R. C. Tsaur, “A fuzzy time series-Markov chain model with an application to forecast the exchange rate between the Taiwan and us Dollar,” *Int. J. Innov. Comput. Inf. Control*, vol. 8, no. 7 B, pp. 4931–4942, 2012.