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ARIMA METHOD IN PREDICTING THE RUPIAH EXCHANGE RATE: THE EFFECT OF DAILY AND MONTHLY DATA FREQUENCY ON THE ACCURACY OF SHORT-TERM PREDICTIONS

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Abstract

The Rupiah exchange rate against the US Dollar (USD) serves as a critical economic indicator influenced by internal and external factors. In time series analysis, the ARIMA (Autoregressive Integrated Moving Average) model is often used to predict the exchange rate. This study examines how data frequency daily versus monthly affects the accuracy of ARIMA predictions for the Rupiah exchange rate. Using historical exchange rate data from Bank Indonesia, this study found that daily data produces more accurate predictions than monthly data based on a comparison of the forecast value with the actual exchange rate on that day. This finding suggests that high volatility in daily data reduces ARIMA's ability to capture short-term patterns, while monthly data provides a more stable pattern for medium-term predictions. This study provides insights for economists, researchers, and practitioners in determining the optimal data frequency for currency exchange rate predictions.

Keywords: ARIMA, Data Frequency, Currency Exchange, Time Series Prediction, Rupiah against Dollar,

Introduction

The exchange rate reflects a country's economic strength and is influenced by factors like inflation, interest rates, and global market dynamics, making it crucial for stakeholders to predict and manage for effective financial strategies and risk mitigation (Ministry of Finance of the Republic of Indonesia, 2024).

The ARIMA model is a popular time series forecasting technique that combines autoregressive (AR), differencing (I), and moving average (MA) elements to predict future values, effectively applied in various economic phenomena such as stock prices, inflation, and currency exchange rates (Box et al., 2015; Mielda et al., 2024; Mubarok.et.al, 2024).

The ARIMA model is widely used to predict currency exchange movements (Wijaya, 2023; Syahputra & Wahyuningsih, 2015; Adesfira.et.al., 2022; Ven & Witanti, 2024), but the impact of data frequency on its performance is often overlooked (Praja.et.al., 2020; Ridwan., et.al., 2023). Daily data is detailed but volatile (Wuri, 2018; Andri, 2016; Nurhasanah & Soeharjoto, 2019; Shahreza, 2017; Azizah, 2020; Darmawan, 2019; Arifin & Mayasya, 2018, Yuliati.et.al, 2023), while monthly data is more stable but may miss short-term dynamics, affecting prediction accuracy in volatile markets (Chatfield, 2004; Handyman, 2014: p8).

This research aims to evaluate the performance of the ARIMA model in predicting the Rupiah exchange rate against USD by comparing two data frequencies: daily and monthly. The analysis was carried out using official historical exchange rate data from Bank Indonesia for the last three years.

Library Survey

Theory and Definition of Exchange Rates

The exchange rate represents the price comparison between currencies and can be categorized into three systems: fixed, managed floating, and free-floating (Syarifuddin, 2015).

The Rupiah exchange rate is the value of Indonesia's currency (IDR) against foreign currencies, such as the US dollar (USD), and its stability is crucial for international trade, foreign investment, and economic stability.

To maintain Rupiah stability, the government enacted Law No. 23 of 1999, amended to Law No. 4 of 2023, assigning Bank Indonesia to ensure Rupiah stability, payment system efficiency, and financial system stability to foster sustainable economic growth.

Definition of Exchange Rates in the Context of ARIMA Predictions

The exchange rate, a dynamic time series influenced by economic, political, and social factors, often exhibits volatility, trends, or seasonality, making ARIMA essential for accurate analysis and predictions.

The ARIMA model, known for its ability to analyze stationary and non-stationary time series, is highly accurate in predicting exchange rates, which significantly impact economic factors like inflation and investment (Box et al., 2015; Islam & Chowdhury, 2022).

JISDOR Exchange Rate

JISDOR is the USD/IDR spot exchange rate based on the interbank transaction rate in Indonesia, calculated in real-time through the Bank Indonesia Foreign Exchange Transaction Monitoring System (SISMONTAVAR). Published since 20 May 2013, it serves as a market reference for USD/IDR spot transactions and is available every working day, excluding weekends and holidays. If no transactions occur, the previous working day's rate is used (Bank Indonesia, n.d).

Daily and Monthly Data

Daily data consists of observations recorded every day, such as exchange rates, stock prices, or temperatures, providing detailed insights into short-term fluctuations and enabling dynamic analysis, like the JISDOR rate, that responds to market changes.

Monthly data is collected or summarized each month, such as inflation figures, CPI, or trade data, and is generally more stable due to its aggregation from daily data, making it ideal for medium to long-term trend analysis.

Data frequency plays a key role in predicting the rupiah exchange rate, with daily data offering high volatility and short-term patterns but requiring more complex pre-processing, while monthly data is more stable, revealing macroeconomic trends and seasonal patterns but losing daily fluctuation details.

ARIMA method analysis of daily and monthly data predictions helps understand how data resolution impacts model accuracy.

Short term forecasting

Short-term forecasting involves estimating a variable's value or trend over a short period, typically under one year, and is commonly used in inventory management, production planning, and marketing strategies (Wheelwright, 1998:21; Hyndman & Athanasopoulos, 2018).

Commonly used techniques for short-term forecasting include time series methods such as *moving averages* and *exponential smoothing* (Chatfield, 2003: p.9). Both techniques rely on past data patterns to predict the future with the assumption that historical patterns will continue in the short term (Hyndman & Athanasopoulos, 2018; Wheelwright, 1998:21).

Short-term forecasting offers higher accuracy than long-term forecasting due to its proximity to actual data, but it struggles with handling significant changes or unexpected events. (Competitive Analytics, n.d; Sandra, 2022).

Long Term Forecasting

Long-term forecasting aims to estimate trends and data patterns over a longer period of time, usually more than one year (Wheelwright, 1998:21). This method is often used in strategic decision making, such as capacity planning, investment and product development (Hyndman & Athanasopoulos, 2018).

Long-term forecasting methods, like regression analysis, ARIMA models, or machine learning, help guide strategic decisions but involve higher uncertainty due to external factors like economic policy, technological change, or global events. (Box & Reinsel, 2015).

Prediction Accuracy

Forecasting accuracy measures how close predicted results are to actual values, influenced by the method, data quality, historical data availability, and appropriate feature selection, with data quality and model complexity significantly affecting the final outcomes.

Error measurements offer insights into model performance, but a deeper evaluation of data characteristics is crucial to assess whether the model can accurately capture historical patterns and predict future outcomes

Research Methodology

Types of research

This research applies a quantitative approach with time series analysis (ARIMA) to analyze and compare the accuracy of the ARIMA model in predicting the Rupiah to US Dollar exchange rate using daily and monthly data.

Data source

The data used in this research is data on the Rupiah exchange rate against the US Dollar obtained from Bank Indonesia. The two types of frequency data used in this research are:

1. Daily Data: Rupiah exchange rate against US Dollars at daily intervals for the period 1 January 2021 to 31 October 2024.
2. Monthly Data: average daily data collected in one month on the JISDOR daily exchange rate data used.

Data analysis

The data analysis compared prediction results between daily and monthly frequencies, measuring and comparing the prediction accuracy of each ARIMA model to assess the impact of data frequency on the results.

Research Limitations

This research focuses solely on the Rupiah-US Dollar exchange rate, excluding other external factors like monetary policy or global economic turmoil, and uses a basic ARIMA model with p, d, and q parameters, without considering alternatives like SARIMA or GARCH. The goal is to offer insights on selecting the optimal data frequency for predicting the Rupiah exchange rate with the ARIMA model.

Research Results and Discussion

Initial Data Understanding and Data Visualization

To understand the initial data, it is necessary to display the daily and monthly exchange rate data as a line graph

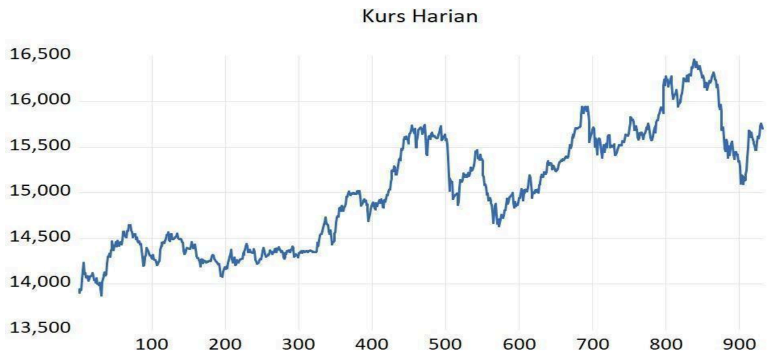

Figure 1.
Daily exchange rate against nominalized date data

From the graph displayed, it is found that the daily data has a high level of volatility which shows a trend graphic pattern.

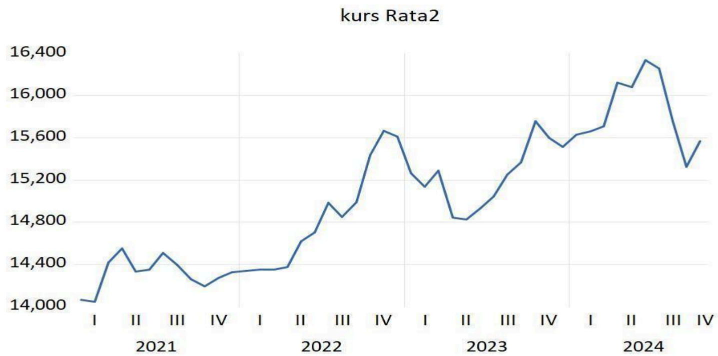

Figure 2.
Monthly exchange rate against the month the data was taken

From the graph displayed, it can be seen that the monthly data also has volatility and shows a trend graphic pattern.

Data Stationarity Test

Stationarity Test on Daily Data

The use of lag in daily data uses the √N rule, where N is the number of observations. Because the number of observations in daily data is 931, the maximum lag used is 30.5 ~ 31 After that, the Augmented Dickey Fuller (ADF) test was carried out with the number of lags observed being 31, including paying attention to intercept patterns and trends. Results obtained:

Null Hypothesis: KURS has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 2 (Automatic - based on SIC, maxlag=31)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.514176	0.3211
Test critical values:	1% level	-3.967969	
	5% level	-3.414664	
	10% level	-3.129485	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(KURS)
Method: Least Squares
Date: 11/30/24 Time: 22:57
Sample (adjusted): 4 931
Included observations: 928 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
KURS(-1)	-0.013630	0.005421	-2.514176	0.0121
D(KURS(-1))	0.131863	0.032732	4.028579	0.0001
D(KURS(-2))	-0.091137	0.032783	-2.779991	0.0055
C	194.6416	76.20407	2.554216	0.0108
@TREND("1")	0.025789	0.012964	1.989271	0.0470

R-squared	0.029654	Mean dependent var	1.917026
Adjusted R-squared	0.025449	S.D. dependent var	50.77667
S.E. of regression	50.12640	Akaike info criterion	10.67235
Sum squared resid	2319181.	Schwarz criterion	10.69839
Log likelihood	-4946.969	Hannan-Quinn criter.	10.68228
F-statistic	7.051819	Durbin-Watson stat	1.992888
Prob(F-statistic)	0.000014		

Figure 3.
Augmented Dickey-Fuller test of daily data

The ADF (Augmented Dickey-Fuller) test results show that the null hypothesis, indicating the exchange rate data has a unit root and is non-stationary, is not rejected. The ADF value of -2.514176 is greater than the critical values at the 1%, 5%, and 10% significance levels, indicating that the daily exchange rate data is not stationary.

Stationarity Test on Monthly Data

The lag of 12, covering one full year, was used for the monthly data to capture seasonal patterns, and the Augmented Dickey Fuller (ADF) test was conducted with 12 lags, considering intercept patterns and trends:

Null Hypothesis: KURS_RATA2 has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.218669	0.0941
Test critical values:	1% level	-4.180911	
	5% level	-3.515523	
	10% level	-3.188259	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(KURS_RATA2)
Method: Least Squares
Date: 11/30/24 Time: 23:39
Sample (adjusted): 2021M03 2024M10
Included observations: 44 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
KURS_RATA2(-1)	-0.380473	0.118208	-3.218669	0.0026
D(KURS_RATA2(-1))	0.368067	0.159555	2.306830	0.0263
C	5368.471	1650.255	3.253116	0.0023
@TREND("2021M01")	16.02575	5.877257	2.726740	0.0094

R-squared	0.225590	Mean dependent var	34.59096
Adjusted R-squared	0.167510	S.D. dependent var	217.6654
S.E. of regression	198.5999	Akaike info criterion	13.50697
Sum squared resid	1577677.	Schwarz criterion	13.66917
Log likelihood	-293.1533	Hannan-Quinn criter.	13.56712
F-statistic	3.884084	Durbin-Watson stat	1.913175
Prob(F-statistic)	0.015814		

Figure 4.
Augmented Dickey-Fuller test daily data 1st differencing

The ADF test results showed that the null hypothesis, which suggests the exchange rate data has a unit root (indicating non-stationarity), was rejected with a statistical value of -3.218669, as it was smaller than the critical value, indicating the data is stationary.

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Data Transformation

Forecasting using the ARIMA method requires stationary data, and since both daily and monthly data failed the ADF test, differencing is applied. A 1st difference is performed on the exchange rate data, considering maximum lag, intercept patterns, and trends. After the stationarity test with ADF, the results for daily data at 1st difference were:

Null Hypothesis: D(KURS) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=30)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-22.33134	0.0000
Test critical values:	1% level	-3.967969	
	5% level	-3.414664	
	10% level	-3.129485	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(KURS,2)
Method: Least Squares
Date: 12/01/24 Time: 00:11
Sample (adjusted): 4 931
Included observations: 928 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(KURS(-1))	-0.973162	0.043578	-22.33134	0.0000
D(KURS(-1),2)	0.098916	0.032731	3.022125	0.0026
C	3.231671	3.316714	0.974359	0.3301
@TREND("1")	-0.002913	0.006161	-0.472787	0.6365

R-squared	0.448179	Mean dependent var	-0.008621
Adjusted R-squared	0.446387	S.D. dependent var	67.56321
S.E. of regression	50.27053	Akaike info criterion	10.67702
Sum squared resid	2335064.	Schwarz criterion	10.69785
Log likelihood	-4950.135	Hannan-Quinn criter.	10.68496
F-statistic	250.1516	Durbin-Watson stat	1.993833
Prob(F-statistic)	0.000000		

Figure 5.
Augmented Dickey-Fuller test daily data 1st differencing

The null hypothesis, suggesting that the exchange rate data has a unit root, is rejected because the ADF test value of the 1st differencing daily data (-22.33134) is smaller than the critical values at 1% (-3.967969), 5% (-3.414664), and 10% (-3.129485), indicating the data is stationary.

The data is considered stationary if the P-value is less than 0.05, as seen in the daily data with a 1st differentiation P-value of 0.0000. Additionally, the Durbin-Watson statistic of 1.993833, close to 2, suggests no significant autocorrelation in the residuals.

Similarly, for the monthly exchange rate data, stationarity is achieved through first differencing, resulting in:

Null Hypothesis: D(KURS_RATA2) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=6)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.532944	0.0002
Test critical values:	1% level	-4.180911	
	5% level	-3.515523	
	10% level	-3.188259	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(KURS_RATA2,2)
Method: Least Squares
Date: 12/01/24 Time: 00:43
Sample (adjusted): 2021M03 2024M10
Included observations: 44 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(KURS_RATA2(-1))	-0.868457	0.156961	-5.532944	0.0000
C	60.83110	70.82830	0.858853	0.3954
@TREND("2021M01")	-1.277264	2.632630	-0.485167	0.6301

R-squared	0.427768	Mean dependent var	5.888688
Adjusted R-squared	0.399854	S.D. dependent var	284.1194
S.E. of regression	220.1046	Akaike info criterion	13.69183
Sum squared resid	1986288.	Schwarz criterion	13.81348
Log likelihood	-298.2202	Hannan-Quinn criter.	13.73694
F-statistic	15.32464	Durbin-Watson stat	1.831174
Prob(F-statistic)	0.000011		

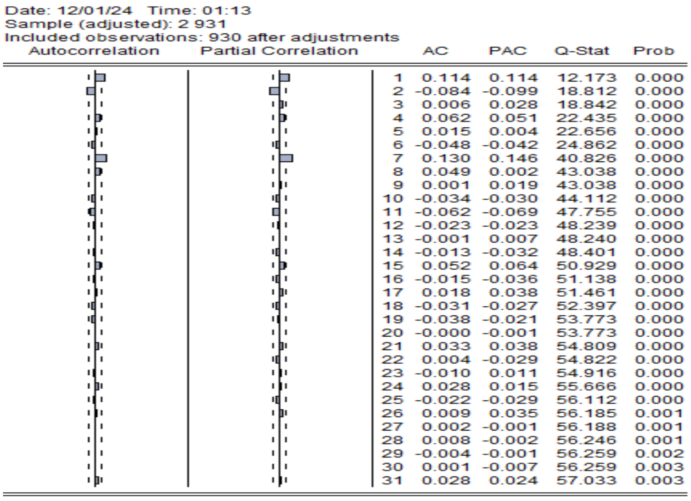
Figure 6.
Augmented Dickey-Fuller test 1st monthly data differentiation

The Augmented Dickey-Fuller (ADF) test results indicate that both daily and monthly exchange rate data are stationary after the first differentiation, meaning the value of d is 1 (p, 1, q).

Autocorrelation Function (ACF) dan Partial Autocorrelation Function (PACF)

ACF and PACF on Kurs daily data

To get the parameter values p, d, q in ARIMA, it is necessary to visualize ACF and PACF graphs from daily exchange rate data. Following are the visualization results:



Date: 12/01/24 Time: 01:13
Sample (adjusted): 2 931
Included observations: 930 after adjustments

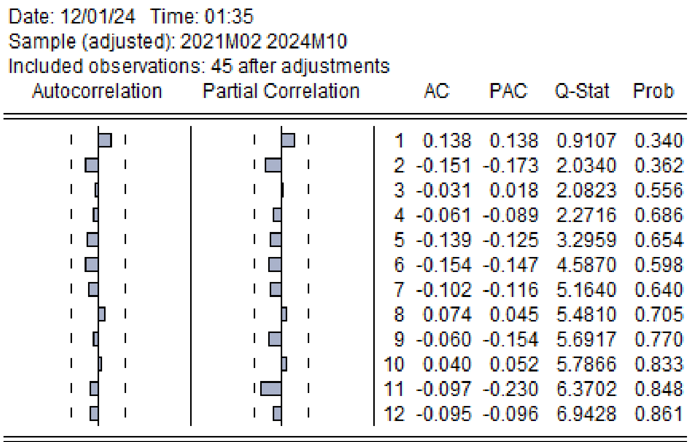
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.114	0.114	12.173	0.000
		2	-0.084	-0.099	18.812	0.000
		3	0.006	0.028	18.842	0.000
		4	0.062	0.051	22.435	0.000
		5	0.015	0.004	22.656	0.000
		6	-0.048	-0.042	24.862	0.000
		7	0.130	0.146	40.826	0.000
		8	0.049	0.002	43.038	0.000
		9	0.001	0.019	43.038	0.000
		10	-0.034	-0.030	44.112	0.000
		11	-0.062	-0.069	47.755	0.000
		12	-0.023	-0.023	48.239	0.000
		13	-0.001	0.007	48.240	0.000
		14	-0.013	-0.032	48.401	0.000
		15	0.052	0.064	50.929	0.000
		16	-0.015	-0.036	51.138	0.000
		17	0.018	0.038	51.461	0.000
		18	-0.031	-0.027	52.397	0.000
		19	-0.038	-0.021	53.773	0.000
		20	-0.000	-0.001	53.773	0.000
		21	0.033	0.038	54.809	0.000
		22	0.004	-0.029	54.822	0.000
		23	-0.010	0.011	54.916	0.000
		24	0.028	0.015	55.666	0.000
		25	-0.022	-0.029	56.112	0.000
		26	0.009	0.035	56.185	0.001
		27	0.002	-0.001	56.188	0.001
		28	0.008	-0.002	56.246	0.001
		29	-0.004	-0.001	56.259	0.002
		30	0.001	-0.007	56.259	0.003
		31	0.028	0.024	57.033	0.003

Figure 7.
ACF and PACF graphs of daily exchange rate data

The ACF and PACF graphs of daily exchange data show threshold crossings at the 1st, 2nd, and 7th lags, indicating possible p and q values of 0.1 and 2, with the 7th lag excluded. The AR value uses a lag from the PACF, while the MA value uses a lag from the ACF.

ACF and PACF on Monthly Exchange rate data

To obtain the parameters p, d, q in ARIMA, ACF and PACF graphs of monthly exchange rate data need to be visualized. The results are as follows:



Date: 12/01/24 Time: 01:35
Sample (adjusted): 2021M02 2024M10
Included observations: 45 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.138	0.138	0.9107	0.340
		2	-0.151	-0.173	2.0340	0.362
		3	-0.031	0.018	2.0823	0.556
		4	-0.061	-0.089	2.2716	0.686
		5	-0.139	-0.125	3.2959	0.654
		6	-0.154	-0.147	4.5870	0.598
		7	-0.102	-0.116	5.1640	0.640
		8	0.074	0.045	5.4810	0.705
		9	-0.060	-0.154	5.6917	0.770
		10	0.040	0.052	5.7866	0.833
		11	-0.097	-0.230	6.3702	0.848
		12	-0.095	-0.096	6.9428	0.861

Figure 8.
ACF and PACF graphs from Monthly Exchange rate data

From the ACF and PACF graphs of monthly exchange rate data, it can be seen that there is no lag that crosses the threshold, therefore the possible p and q values are 0. So the AR (autoregressive) value uses the lag in PACF and the MA (Moving Average) value uses the value 0 (zero).

Evaluation of Daily Exchange Rate Models

Evaluation of the daily exchange rate ARIMA model

An ARIMA (p, d, q) model for daily exchange rates was created using ADF, ACF, and PACF visualizations, with d set to 1. Based on ACF and PACF results, the data falls between values 0, 1, and 2, leading to initial models of ARIMA (0,1,0), ARIMA (0,1,1), ARIMA (1,1,0), and ARIMA (1,1,1).

Evaluation of ARIMA Model (0,1,0) Daily Data

After determining the model, a model evaluation was carried out against the ARIMA (0,1,0) model, with the following results:

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Dependent Variable: KURS
Method: Least Squares
Date: 12/01/24 Time: 02:03
Sample: 1 931
Included observations: 931

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	15026.51	21.06980	713.1774	0.0000

R-squared	0.000000	Mean dependent var	15026.51
Adjusted R-squared	0.000000	S.D. dependent var	642.8880
S.E. of regression	642.8880	Akaike info criterion	15.77089
Sum squared resid	3.84E+08	Schwarz criterion	15.77609
Log likelihood	-7340.350	Hannan-Quinn criter.	15.77287
Durbin-Watson stat	0.006232		

Figure 9.
ARIMA (0,1,0) model on daily data

After the residual diagnostic, a normal distribution test showed a p-value of 0, which is less than α=0.05, indicating that the residuals are not normal and the model may need improvement.
Evaluation of ARIMA Model (0,1,1) Daily Data
Next, an evaluation was carried out on the ARIMA model (0,1,1) with the following results:

Dependent Variable: KURS
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 12/01/24 Time: 04:24
Sample: 1 931
Included observations: 931
Convergence achieved after 26 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	15026.40	22.10423	679.7975	0.0000
MA(1)	0.977440	0.007774	125.7254	0.0000
SIGMASQ	110028.0	7129.300	15.43322	0.0000

R-squared	0.733499	Mean dependent var	15026.51
Adjusted R-squared	0.732924	S.D. dependent var	642.8880
S.E. of regression	332.2405	Akaike info criterion	14.45615
Sum squared resid	1.02E+08	Schwarz criterion	14.47174
Log likelihood	-6726.339	Hannan-Quinn criter.	14.46210
F-statistic	1277.079	Durbin-Watson stat	0.154972
Prob(F-statistic)	0.000000		
Inverted MA Roots	-.98		

Figure 10.
ARIMA (0,1,1) model on daily data

The normal distribution test shows a p-value of 0, less than α=0.05, indicating non-normal residuals and suggesting the model may need improvement.
Evaluation of the ARIMA Model (1,1,0) Daily Data
Next, an evaluation was carried out on the ARIMA model (1,1,0) with the following results:

Dependent Variable: KURS
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 12/01/24 Time: 04:48
Sample: 1 931
Included observations: 931
Convergence achieved after 8 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	14920.20	432.8880	34.46665	0.0000
AR(1)	0.997658	0.002243	444.7908	0.0000
SIGMASQ	2573.582	73.50452	35.01257	0.0000

R-squared	0.993766	Mean dependent var	15026.51
Adjusted R-squared	0.993753	S.D. dependent var	642.8880
S.E. of regression	50.81242	Akaike info criterion	10.70314
Sum squared resid	2396005.	Schwarz criterion	10.71872
Log likelihood	-4979.311	Hannan-Quinn criter.	10.70908
F-statistic	73972.15	Durbin-Watson stat	1.768483
Prob(F-statistic)	0.000000		
Inverted AR Roots	1.00		

Figure 11.
ARIMA (0,1,1) model on daily data

The ARIMA (1,1,0) model is still being tested for forecasting due to the absence of autocorrelation and the need to assess its accuracy.

Evaluation of the ARIMA Model (1,1,1) Daily data
Next, an evaluation of the ARIMA model (1,1,1) was carried out with the following results:

Dependent Variable: KURS
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 12/01/24 Time: 05:02
Sample: 1 931
Included observations: 931
Convergence achieved after 18 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	14934.42	394.7160	37.83587	0.0000
AR(1)	0.996854	0.002589	385.0534	0.0000
MA(1)	0.142760	0.026860	5.315011	0.0000
SIGMASQ	2530.689	72.40222	34.95319	0.0000

R-squared	0.993870	Mean dependent var	15026.51
Adjusted R-squared	0.993851	S.D. dependent var	642.8880
S.E. of regression	50.41437	Akaike info criterion	10.68847
Sum squared resid	2356071.	Schwarz criterion	10.70925
Log likelihood	-4971.483	Hannan-Quinn criter.	10.69640
F-statistic	50101.80	Durbin-Watson stat	2.024935
Prob(F-statistic)	0.000000		

Inverted AR Roots	1.00
Inverted MA Roots	-.14

Figure 12.
ARIMA (1,1,1) model on daily data

The ARIMA (1,1,1) model combines the strengths of ARIMA (1,1,0) with autoregression and adds the moving average (MA (1)) to handle error fluctuations, making it more flexible and accurate for short-term analysis. However, if MA (1) offers little benefit, the ARIMA (1,1,0) model can be a simpler alternative.

The results indicate that the model residuals are not white noise, with significant autocorrelation at many lags, suggesting the model has not fully explained the data pattern.

The evaluation results indicate that the ARIMA (1,1,1) model is suitable for forecasting.

Forecasting Daily Exchange Rate Data

Forecasting tests using the ARIMA (1,1,0) model were conducted for a 1-day exchange rate forecast. The predicted exchange rate was Rp. 14,085.33, while the actual rate on November 1, 2024, was Rp. 15,723, resulting in a difference of Rp. 1,637.67, corresponding to an accuracy of 89.58%

A forecasting test using the ARIMA model (1,1,1) predicted the exchange rate for the next day at IDR 14,879.50, while the actual JISDOR exchange rate on November 1 was IDR 15,723, showing a difference of IDR 843.50, with an accuracy of 94.64%.

The ARIMA (1,1,1) model is more accurate than the ARIMA (1,1,0) model, with a prediction accuracy of 94.64% for daily exchange rate data

Evaluation of the ARIMA model for monthly exchange rates

An ARIMA (p, d, q) model for monthly exchange rates was developed, with differencing (d) set to 1, based on ADF, ACF, and PACF visualizations. The data shows values between 0, 1, and 2, leading to initial attempts with p and q between 0 and 1, resulting in models ARIMA (0,1,0), ARIMA (0,1,1), ARIMA (1,1,0), and ARIMA (1,1,1).

Evaluation of the ARIMA Model (0,1,0) Monthly Data

After determining the model, a model evaluation was carried out against the ARIMA (0,1,0) model, with the following results:

Dependent Variable: KURS_BULANAN
Method: Least Squares
Date: 12/02/24 Time: 15:44
Sample: 2021M01 2024M10
Included observations: 46

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	15026.99	94.98373	158.2059	0.0000

R-squared	0.000000	Mean dependent var	15026.99
Adjusted R-squared	0.000000	S.D. dependent var	644.2110
S.E. of regression	644.2110	Akaike info criterion	15.79543
Sum squared resid	18675351	Schwarz criterion	15.83518
Log likelihood	-362.2949	Hannan-Quinn criter.	15.81032
Durbin-Watson stat	0.111925		

Figure 13.
ARIMA (0,1,0) model on Monthly data

Therefore, the results of the ARIMA model analysis (0,1,0) are:

1. The ARIMA (0,1,0) model is unsuitable for this data due to its zero R-squared, high standard error, and autocorrelated residuals (low Durbin-Watson).
2. Short-term predictions are unreliable due to the model's poor pattern recognition.
3. A model is needed to accommodate larger AR or MA parameters, such as ARIMA (0,1,1), ARIMA (1,1,0), or ARIMA (1,1,1).

Evaluation of ARIMA Model (0,1,1)

An evaluation of the ARIMA (0,1,1) model using monthly data yielded the following results:

Dependent Variable: KURS_BULANAN
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 12/02/24 Time: 16:29
Sample: 2021M01 2024M10
Included observations: 46
Convergence achieved after 25 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	15031.05	105.3540	142.6719	0.0000
MA(1)	0.886880	0.115432	7.683165	0.0000
SIGMASQ	142743.7	37463.44	3.810212	0.0004

R-squared	0.648402	Mean dependent var	15026.99
Adjusted R-squared	0.632049	S.D. dependent var	644.2110
S.E. of regression	390.7717	Akaike info criterion	14.87069
Sum squared resid	6566208.	Schwarz criterion	14.98995
Log likelihood	-339.0259	Hannan-Quinn criter.	14.91537
F-statistic	39.64946	Durbin-Watson stat	0.655092
Prob(F-statistic)	0.000000		
Inverted MA Roots	-.89		

Figure 14.
ARIMA (0,1,1) model on Monthly data

Therefore, the results of the ARIMA model analysis (0,1,1) are:

1. Model Performance: The ARIMA (0,1,1) model is quite good, with R^2 around **64.84%**, but there is still room for improvement, especially regarding residuals (low Durbin-Watson).
2. The model outperforms ARIMA (0,1,0) for short-term prediction, but residual autocorrelation suggests suboptimal performance.
3. Consider models with other parameter combinations, for example ARIMA (1,1,1).
4. This model can be used for short-term analysis, but the results may not be as accurate as expected because there is still autocorrelation in the residuals

Evaluation of ARIMA Model (1,1,0)

Next, an evaluation was carried out on the ARIMA model (1,1,0) with monthly data, the following results were obtained:

Dependent Variable: KURS_BULANAN
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 12/02/24 Time: 18:52
Sample: 2021M01 2024M10
Included observations: 46
Convergence achieved after 7 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	14931.02	411.1014	36.31956	0.0000
AR(1)	0.949576	0.044767	21.21166	0.0000
SIGMASQ	45410.03	10077.10	4.506260	0.0001

R-squared	0.888149	Mean dependent var	15026.99
Adjusted R-squared	0.882946	S.D. dependent var	644.2110
S.E. of regression	220.4046	Akaike info criterion	13.74223
Sum squared resid	2088861.	Schwarz criterion	13.86149
Log likelihood	-313.0712	Hannan-Quinn criter.	13.78690
F-statistic	170.7196	Durbin-Watson stat	1.603716
Prob(F-statistic)	0.000000		
Inverted AR Roots	.95		

Figure 14.
ARIMA (1,1,0) model on Monthly data

Therefore, the results of the ARIMA model analysis (1,1,0) are:

1. ARIMA model (1,1,0**)** showed excellent performance with R^2 = 88.81, residual variance is low, and Durbin-Watson is close to 2.
2. The model outperforms ARIMA (0,1,0) and ARIMA (0,1,1) in short-term predictions, showing lower residual error and a better data fit.
3. This model is suitable for short-term analysis, but needs to be compared with other models such as ARIMA (1,1,1).

Evaluation of ARIMA Model (1,1,1)

Next, an evaluation was carried out on the ARIMA model (1,1,0) with monthly data, the following results were obtained:

Dependent Variable: KURS_BULANAN
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 12/02/24 Time: 20:04
Sample: 2021M01 2024M10
Included observations: 46
Convergence achieved after 28 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	14974.84	353.9693	42.30548	0.0000
AR(1)	0.920637	0.057839	15.91715	0.0000
MA(1)	0.275764	0.173456	1.589819	0.1194
SIGMASQ	43209.71	9686.546	4.460796	0.0001

R-squared	0.893568	Mean dependent var	15026.99
Adjusted R-squared	0.885966	S.D. dependent var	644.2110
S.E. of regression	217.5429	Akaike info criterion	13.73806
Sum squared resid	1987646.	Schwarz criterion	13.89707
Log likelihood	-311.9754	Hannan-Quinn criter.	13.79763
F-statistic	117.5399	Durbin-Watson stat	1.967169
Prob(F-statistic)	0.000000		
Inverted AR Roots	.92		
Inverted MA Roots	-.28		

Figure 15.
ARIMA (1,1,0) model on Monthly data

Therefore, the results of the ARIMA model analysis (1,1,1) are:

1. The ARIMA (1,1,1) model performs excellently with an R-square of 89.36%, low residual standard error, and no significant autocorrelation in the residuals.
2. This model outperforms ARIMA (1,1,0) and ARIMA (0,1,1) with smaller residuals, higher log likelihood, and lower AIC.
3. The MA (1) variable is insignificant (Prob = 0.1194), so ARIMA (1,1,0) may offer a simpler model with minimal accuracy loss.
4. This model is ideal for short-term analysis, especially with a dominant autoregressive pattern, but requires additional diagnostics like residual ACF/PACF to confirm all data patterns are captured.
5. ARIMA (1,1,1) provides stable, accurate, and relevant short-term predictions for this dataset.

Forecasting Monthly Exchange Rate Data

The exchange rate for November 2024 will be predicted one month in advance using daily exchange rate data for November, averaged, and compared with the forecasting results of the ARIMA (1,1,0) and ARIMA (1,1,1) models.

Table 1
JISDOR Daily Exchange Rates for November 2024

Informasi Kurs Jisdor		
NO	Tanggal	Kurs
1	11/29/2024 12:00:00 AM	15.856,00
2	11/28/2024 12:00:00 AM	15.864,00
3	11/26/2024 12:00:00 AM	15.930,00
4	11/25/2024 12:00:00 AM	15.864,00
5	11/22/2024 12:00:00 AM	15.911,00
6	11/21/2024 12:00:00 AM	15.942,00
7	11/20/2024 12:00:00 AM	15.858,00
8	11/19/2024 12:00:00 AM	15.816,00
9	11/18/2024 12:00:00 AM	15.848,00
10	11/15/2024 12:00:00 AM	15.888,00
11	11/14/2024 12:00:00 AM	15.873,00
12	11/13/2024 12:00:00 AM	15.782,00
13	11/12/2024 12:00:00 AM	15.771,00
14	11/11/2024 12:00:00 AM	15.677,00
15	11/8/2024 12:00:00 AM	15.671,00
16	11/7/2024 12:00:00 AM	15.767,00
17	11/6/2024 12:00:00 AM	15.840,00
18	11/5/2024 12:00:00 AM	15.766,00
19	11/4/2024 12:00:00 AM	15.751,00
20	11/1/2024 12:00:00 AM	15.723,00

Forecasting tests using the ARIMA (1,1,0) model predict a value of Rp. 14,850.59 for the next month, with a 93.87% accuracy when compared to the November 2024 exchange rate of Rp. 15,819.90, showing a difference of Rp. 969.31.

A forecasting test using the ARIMA (1,1,1) model predicted an exchange rate of IDR 14,953.91 for the next month, showing a difference of IDR 865.99 from the November 2024 exchange rate of IDR 15,819.90, resulting in an accuracy of approximately 94.53%.

From the comparison of the two data, it can be seen that the ARIMA (1,1,1) model is more accurate than the ARIMA (1,1,0) model. The accuracy of the ARIMA Model (1,1,1) in predicting daily exchange rate data is 94.53%.

Research Results

The research on the accuracy of daily and monthly data for short-term forecasting yielded the following results:

Table 2
Accuracy Level of Daily and Monthly ARIMA Models

No.	ARIMA Models	Accuracy Percentage
1.	ARIMA Model (1,1,0) Daily	89,58%
2.	ARIMA Model (1,1,1) Daily	94,64 %
3.	ARIMA Model (1,1,0) Monthly	93,87%
4.	ARIMA Model (1,1,1) Monthly	94,53%

The ARIMA (1,1,1) model shows the best performance for both daily and monthly data, with accuracy rates of 94.64% and 94.53%, respectively, with daily data slightly outperforming monthly data.

The ARIMA (1,1,0) model shows better accuracy for monthly data (93.87%) compared to daily data (89.58%), as aggregated monthly fluctuations make pattern identification easier.

When selecting the ARIMA model for short-term forecasting, consider the data frequency; ARIMA (1,1,1) is ideal for daily data, while monthly data offers similar prediction stability.

Conclusion

Daily Data Frequency

The ARIMA model using daily data shows higher prediction accuracy than the monthly data model, indicating greater sensitivity to daily fluctuations in the Rupiah exchange rate.

Monthly Data Frequency

The ARIMA model with monthly data offers more stable results but lower prediction accuracy, as it loses daily exchange rate details and fails to capture short-term fluctuations.
Using daily data is recommended for predicting the Rupiah exchange rate to achieve higher accuracy in a short period.

Suggestions

a. Data Frequency Selection.
b. Use of Other ARIMA Models: To improve accuracy, it is recommended to explore more complex ARIMA models, such as SARIMA (Seasonal ARIMA) or GARCH (Generalized Autoregressive Conditional Heteroskedasticity).
c. Consideration of External Factors.
d. Increased Study Period.
e. Exploration of Data Variations

Reference

Andri, Gustiva. (2016). *Analysis of the determinants of the volatility of the rupiah exchange rate against the US dollar for the 1993-2014 period* (S1 thesis). Yogyakarta Muhammadiyah University.

Ardesfira, G., Zedha, H. F., Fazana, I., Rahmadhiyanti, J., Rahima, S., & Anwar, S. (2022). Forecasting the rupiah exchange rate against the US dollar using the autoregressive integrated moving average (ARIMA) method. *Jambura Journal of Probability and Statistics*, 3(2). https://doi.org/10.34312/jjps.v3i2.15469 ;

Arifin, I., & Hadi, G. (2007). *Opening economic horizons for SMA/MA class XII social sciences program* (Volume 3, Edition 1, 1st Printing). Bandung: PT Setia Purna Investments ;

Arifin, S., & Mayasya, S. (2018). Factors that influence the rupiah exchange rate against the United States dollar. *Qu-Economic Journal*, 8(1). https://doi.org/10.35448/jequ.v8i1.4965

Azizah, Nurul. Analysis of Volatility Transmission in the Indonesian Financial Market. Bachelor thesis, University of Borneo Tarakan, 2020 ;

Bank Indonesia. (n.d.). *Monetary Policy*. Retrieved November 24, 2024, from https://www.bi.go.id/id/fungsi-utama/moneter/default.aspx ;

Bank Indonesia. (n.d.). *Exchange rate information*. Retrieved November 29, 2024, from https://www.bi.go.id/id/fungsi-utama/moneter/informasi-kurs/default.aspx ;

Box, G. E. P., Jenkins, G. M., & Reinsel, G. C. (2015). *Time series analysis: Forecasting and control* (5th ed.). Wiley ;

Chatfield, C. (2004). *The analysis of time series: An introduction* (6th ed.). CRC Press. https://doi.org/10.1201/9780203491683 ;

Competitive Analytics. (n.d.). *Short-term vs long-term forecast methods: Choosing the right path for accurate predictions*. Competitive Analytics. Retrieved November 30, 2024, from https://competitiveanalytics.com/short-term-vs-long-term-forecast-methods ;

Darmawan, B. (2019). *Forecasting the volatility of rupiah exchange rate return data against the dollar using the Integrated Generalized Autoregressive Conditional Heteroscedasticity (IGARCH) method* (S1 thesis). Bandar Lampung University.

Darsono, & Rahman, R. E. (n.d.). *Management of exchange rates and foreign capital flows* [PDF]. Bank Indonesia Institute. Retrieved November 24, 2024, from https://www.bi.go.id/id/bi-institute/policy-mix/core/Documents/Pengelolaan%20NT%20dan%20Aliran%20Modal%20Asing.pdf ;

Deliarnov. (2007). *Socioeconomic knowledge for middle school and MTs class IX*. Jakarta: Erlangga Publishers;

Eco, Y. (2009). *Economics 2: For SMA and MA Class XI*. Jakarta: Book Center, Department of National Education;

Ministry of Finance of the Republic of Indonesia. (2024). *Press Release Financial System Stability*. Retrieved November 16, 2024 from https://www.kemenkeu.go.id/informasi-publik/publikasi/siaran-pers/Siaran-Pers-Stabilitas-Sistem-Keuangan-%281%29 ;

Levi, Maurice D. 1996. International Finance. Yogyakarta: Andi Offset ;

Madura, J. (2008). *International Financial Management*. 9th Edition. Boston: Thomson South-Western;

Mishkin, F. S., Matthews, K., & Giuliodori, M. (2013). *The economics of money, banking, and financial markets* (European ed.). Pearson ;

Mubarok, F., Purnamasari, I., & Yuniarti, D. (2024). Forecasting the Rupiah exchange rate against the US Dollar using the Autoregressive Integrated Moving Average model. *Journal of Mathematics: Theory and Applications (JOMTA)*, 6(2), 225–236. https://doi.org/10.31605/jomta.v6i2.4072;

Mukhlis, I. (2011). Analysis of the volatility of the rupiah exchange rate against the dollar. *Journal of Indonesian Applied Economics*, 5(2). Retrieved from https://media.neliti.com/media/publications/37945-ID-analisis-volatilitas-nilai-tukar-mata-uang-rupiah-terhadap-dolar.pdf ;

Md Shahidul & Chowdhury, Tasnim. (2022). Application of ARIMA Model in Forecasting Exchange Rate: Evidence from Bangladesh. Asian Journal of Managerial Science. 11. 33-40. 10.51983/ajms-2022.11.2.3325 ;

Nurhasanah, A. I., & Soeharjoto. (2019). Determination of the volatility of the rupiah exchange rate against the US dollar. *Journal of Accounting, Economics and Business Management*, 7(1), 1–8. https://doi.org/10.24071/jakem.2019.070101;

Praja, A. S., Harsa, H., Makmur, E. E. S., Sudewi, R. S. S., & Permana, D. S. (2020). Rainfall prediction performance using seasonal ARIMA on three types of rain patterns in Indonesia. *Meteorology, Climatology and Geophysics Agency*.

Ridwan, M., Sadik, K., & Afendi, F. M. (2023). Comparison of ARIMA and GRU models for high-frequency time series forecasting. *Scientific Journal of Informatics*, 10(3). http://journal.unnes.ac.id/nju/index.php/sji ;

Salim, J. (2010). *10 easiest & safest investments* (W. Oktavia, Ed.). Jakarta: VisiMedia;

Sarda, B. (2022, November 30). *Understanding cash flow forecasting methods: Short term vs. long term*. HighRadius. Retrieved November 30, 2024, from https://www.highradius.com/resources/Blog/short-vs-long-term-cash-forecasting/

Sumarjaya, I. W., & Susilawati, M. (2024). A comparative analysis of Deep Autoregressive, Deep State Space, Simple Feed Forward, and Seasonal Naive in forecasting Indonesia's inflation rate. *Journal of Mathematics*, 14(1), 37–51. https://doi.org/10.24843/JMAT.2024.v14.i01.p170 ;

Simorangkir, I., & Suseno, T. (2004). *Exchange rate systems and policies* (Central Bank Series No. 12). Central Bank Education and Study Center (PPSK) Bank Indonesia;

Sukardi. (2009). *Economics 2: For SMA/MA Class XI* (Titik Maryani, Ed.; Haryana Humardani, Ilustr.). Jakarta: Book Center, Department of National Education.

Sukirno, S. (1981). *Introduction to macroeconomic theory*. Jakarta: LP3ES.

Supriyanto, & Muhson, A. (2009). *Economics 1: For SMA and MA Class X* (T. Mulyadi, Ed.). Jakarta: Book Center, Department of National Education.

Syahputra, I., Irawan, M. I., & Wahyuningsih, N. (2015). Application of the memetic algorithm for forecasting foreign exchange rate movements using the ARIMA (Box-Jenkins) model. *ITS Science and Arts Journal*, 4(2), 1–8.

Syarifuddin, F. (2015). *Concept, dynamics and response to exchange rate policy in Indonesia* (Central Bank Series No. 24). Bank Indonesia Institute. https://www.bi.go.id/id/edukasi/Documents/BSK-24-Nilai-Tukar-Ferry.pdf

Shahreza, D. (2017). Volatility of the rupiah exchange rate against the dollar during the 2 years of the Jokowi-JK administration: Application of the ARIMA model. *Journal of Management and Business Research (JRMB)*, 2(S1), 215–226. https://doi.org/10.24071/jrmb.v2i1.154

Vean, A. C., & Witanti, A. (2024). Predict the rupiah exchange rate against the euro and pound using ARIMA. *Dinarek Journal*, 20(1), 39–47. http://jurnal.dinarek.unsoed.ac.id

Wijaya, A. R. (2023). Forecasting the rupiah exchange rate against the US dollar using the ARIMA model. *MIMS: Journal of Mathematics and Informatics*, 23(2), 188-199 https://doi.org/10.19184/mims.v23i2.38660 ;

Wuri, J. (2018). Fluctuations in foreign exchange rates in several Southeast Asian countries. *EXERO: Journal of Research in Business and Economics*, 1(1), 1–10. https://doi.org/10.24071/exero.2018.010101;

Yuliyati, I., Yusuf, A. A., & Azis, A. (2023). Analysis of the determinants of the volatility of the rupiah exchange rate in Indonesia 2010-2022. *INCLUSIVE: Journal for the Study of Islamic Economics and Law Research*, 8(1). https://doi.org/10.24014/inkl.v8i1.13417 ;

Wheelwright, S., Makridakis, S., & Hyndman, R.J. (1998). Forecasting: Methods and Applications, 3rd Edition.