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Implementation of Hybrid Autoregressive Fractionally Integrated Moving Average-Neural Network (ARFIMA-NN) Model for Forecasting the Jakarta Composite Index

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Keywords: Forecast, *Hybrid* ARFIMA-NN, JCI.

Abstract:

Extreme fluctuations in the closing price of the Jakarta Composite Index (JCI) on the Indonesia Stock Exchange (IDX) have created unpredictable uncertainty. Therefore, forecasting JCI closing prices can assist investors in anticipating investment risks and determining future investment strategies. This study implements a hybrid Autoregressive Fractionally Integrated Moving Average-Neural Network (ARFIMA-NN) model, chosen for its capability to handle long-memory characteristics and capture non-linear patterns, which is expected to enhance forecasting accuracy. Based on the analysis, the hybrid ARFIMA-NN models using 1 to 3 neurons yielded forecasting results with a MAPE below 10%, it shows very high forecasting accuracy. Furthermore, the hybrid ARFIMA (1; 0.51; 4)-NN 2 model, trained on JCI data from January 2005 to December 2024, predicts that the JCI for the period of January to December 2025 will show a month-to-month increase.

1. Introduction

Forecasting in statistics aims to predict future events or trends through analysis of past data (Nurmayanti et al., 2023). Time series analysis is considered one of the most widely used methods of forecasting today. This method analyzes data based on a fixed time frequency, whether on a daily, weekly, monthly, annual, or other time scale (Ardesfira et al., 2022).

Forecasting methods such as Autoregressive Integrated Moving Average (ARIMA), decomposition, exponential smoothing, or regresision have limitations in processing data that contain long memory characteristics or long-term dependencies (Hanifa et al., 2021). The Autoregressive Fractionally Integrated Moving Average (ARFIMA) model can be used to handle long-memory phenomena characterized by slow or hyperbolic decline patterns in the Autocorrelation Function (ACF) graph (Akbar & Kharisudin, 2020).

The ARFIMA model was developed by Granger and Joyeux in 1980 as an extension of the ARIMA model. Unlike ARIMA, which uses integer differencing (short memory), ARFIMA is capable of performing differencing on fractional values, thereby enabling it to model both short-term and long-term data dependencies (Akbar & Kharisudin, 2020). The differencing parameters in the ARFIMA model can be estimated using the Geweke and Porter-Hudak (GPH) method, which is more flexible than the Maximum Likelihood or Nonlinear Least Square methods, because the distinguishing parameters can be estimated directly without first determining the p and q parameters (Oktaviani & Rifai, 2024). The application of ARFIMA with the GPH method has been carried out by

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Akbar and Kharisudin (2018) and has successfully predicted wind speed with a MAPE value of 10.45%, which is considered good accuracy.

The Neural Network (NN) method is a data processing scheme that resembles the neural network of living creatures (Siang, 2005). One of the training algorithms, backpropagation, is a supervised learning technique that is often used to train networks by adjusting the weights in the input, hidden, and output layers (Hasanah & Permatasari, 2020). The implementation of NN in the research by Rahmah, Hayati, and Cahyaningsih (2025) shows that the NN architecture with 5 layers in the hidden layer has a MAPE value of 2.08%, which is considered excellent accuracy.

Several studies show that the hybrid approach can improve forecasting accuracy. This is evidenced by research conducted by Buhungo, Hasan, and Nurwan (2024), in which the ARFIMA-ANN hybrid model with the backpropagation algorithm produced a MAPE accuracy of 1.01%, which was better than the single ARFIMA model with a MAPE of 1.73%. Therefore, this study implements the ARFIMA-NN hybrid model on JCI data, which serves as the main indicator of the capital market and the national economy on the IDX (Rosilawati et al., 2023).

Based on this, the ARFIMA-NN hybrid model was implemented on JCI data because this model is capable of handling long memory characteristics and has the ability to capture non-linear patterns, thereby improving forecasting accuracy.

2. Literature Review

2.1. Autoregressive Fractionally Integrated Moving Average (ARFIMA)

In time series analysis, the ARFIMA model is used as a solution to overcome the limitations of the ARIMA model in explaining long-term phenomena in data. The main characteristic that distinguishes the ARIMA and ARFIMA models lies in their distinguishing parameters. While the parameter *d* in the ARIMA model is restricted to an integer, the ARFIMA model allows for a fractional value of *D* (Melani et al., 2022). The ARFIMA (*p*, *D*, *q*) model is as follows (Krismawanti et al., 2019):

$$\phi_p(B)(1-B)^D Z_t = \theta_q(B)e_t \tag{1}$$

The long memory characteristic of the data is represented by the discriminant filter $(1-B)^D$ in the ARFIMA model. This operator can be described through binomial series expansion as follows (Oktaviani & Rifai, 2024):

$$(1-B)^D = \sum_{k=1}^{\infty} \binom{D}{k} (-1)^k B^k \tag{2}$$

by:

$$\binom{D}{k} = \frac{D!}{(D-k)!k!} = \frac{\Gamma(D+1)}{\Gamma(k+1)\Gamma(D-k+1)} \tag{3}$$

Description:

$\Gamma(x)$: gamma function

2.2. Estimation of Parameter D Using the Geweke and Poter-Hudak Method

The Geweke and Porter-Hudak (GPH) estimation is one of the most commonly used methods for measuring the integration parameter of the *D* fraction. The GPH method facilitates the direct estimation of the *D* parameter, bypassing the need for an underlying knowledge of the model's specific order of AR(*p*) or MA(*q*) (Fitri et al., 2023). The GPH method is carried out by forming spectral equations, as follows (Winanti et al., 2023):

$$\ln\left|I_z\left(\omega_j\right)\right| = \beta_0 + \beta_1 \ln\left[\left(2\sin\left(\frac{\omega_j}{2}\right)\right)^{-2}\right] + e_j \tag{4}$$

where the value *D* is the estimated value of β_1. The steps are explained below:

1) Determining the harmonic frequency value

$$\omega_j = \frac{2\pi j}{n}, j = 1, 2, ..., m \tag{5}$$

with $\pi = 3,14$ and optimal bandwidth (*m*) limited to $m = n^{0,5}$ where *n* shows the total number of observations.

2) Determining the periodogram value

$$I_z\left(\omega_j\right) = \frac{1}{2\pi}\left\{\gamma_0 + 2\sum_{k=1}^{n-1}\gamma_k \cos\left(j\omega_j\right)\right\}, j = 1, 2, ..., m \tag{6}$$

with $\pi = 3,14$ and γ_k is the autocovariance of lag *t*

Determine the values γ_0 and γ_k using the formula

$$\gamma_0 = \frac{\sum_{t=1}^{n}\left(Z_t - \bar{Z}\right)^2}{n} \tag{7}$$

$$\gamma_k = \rho_k \times \gamma_0 \tag{8}$$

3) Determining predictor variables

$$X_j = \ln\left(\frac{1}{4\sin^2\left(\frac{\omega_j}{2}\right)}\right), j = 1, 2, ..., m \tag{9}$$

4) Determining response variables

$$Y_j = \ln\left[I_z\left(\omega_j\right)\right], j = 1, 2, ..., m \tag{10}$$

5) Determining the estimated value of *D*

$$\hat{\beta}_1 = D = \frac{\sum_{j=1}^{m}\left(X_j - \bar{X}\right)\left(Y_j - \bar{Y}\right)}{\sum_{j=1}^{m}\left(X_j - \bar{X}\right)^2} \tag{11}$$

2.3. Neural Network (NN)

Neural networks are an intelligent computing architecture that adopts neurons as the basic processing elements in human brain architecture. These units are connected through connection weights, enabling signal transmission and gradual information processing. Through the training process, NNs are able to organize themselves to produce consistent responses to inputs, where the output from one neuron can be the final result or input for the next layer of neurons (Pradana et al., 2022).

2.4. Jakarta Composite Index

The Stock Price Index is a statistical instrument that represents the dynamics of price movements of selected stock portfolios that meet specific criteria (Budi, 2021). For investors, index movements are a key indicator for directly monitoring market dynamics and evaluating historical data for investment decisions. Therefore, the presentation of index information is crucial for producing data that is simple, consistent, and easy for investors to understand amid the complexity of stock exchange transactions (Wairooy & Ali, 2019).

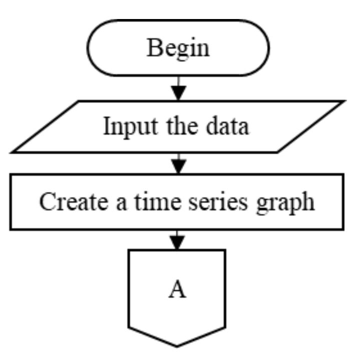
3. Research Method

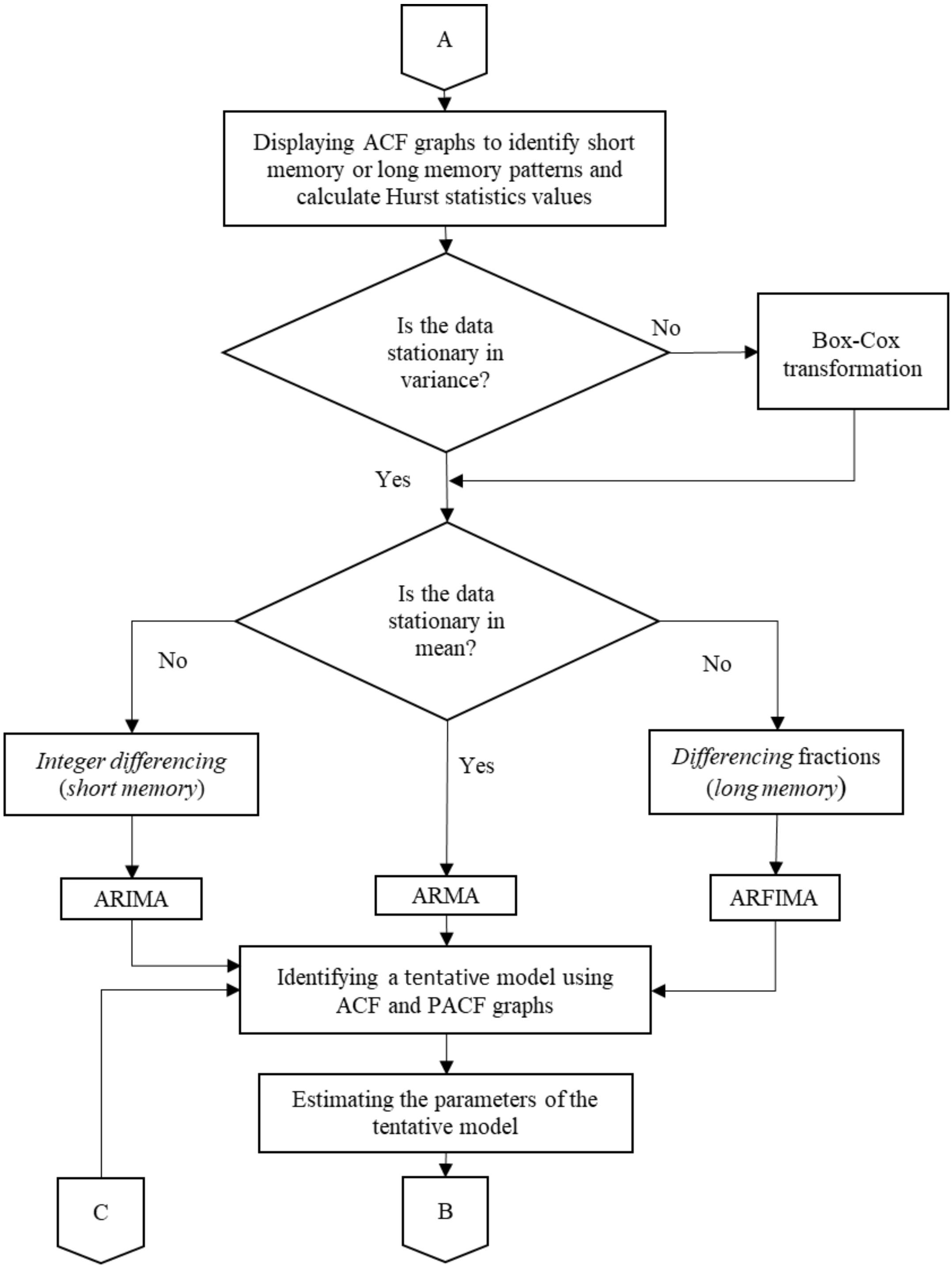
3.1. Data Source

The data used in this study are the monthly closing prices of the Jakarta Composite Index (JCI) from January 2005 to December 2024, totaling 240 data points, sourced from https://id.investing.com/.

3.2. Data Analysis Techniques

Data analysis techniques are presented in a research flowchart shown in the following figure.




A
Displaying ACF graphs to identify short memory or long memory patterns and calculate Hurst statistics values
Is the data stationary in variance?
No
Box-Cox transformation
Yes
Is the data stationary in mean?
No
No
Integer differencing (short memory)
Yes
Differencing fractions (long memory)
ARIMA
ARMA
ARFIMA
Identifying a tentative model using ACF and PACF graphs
Estimating the parameters of the tentative model
C
B

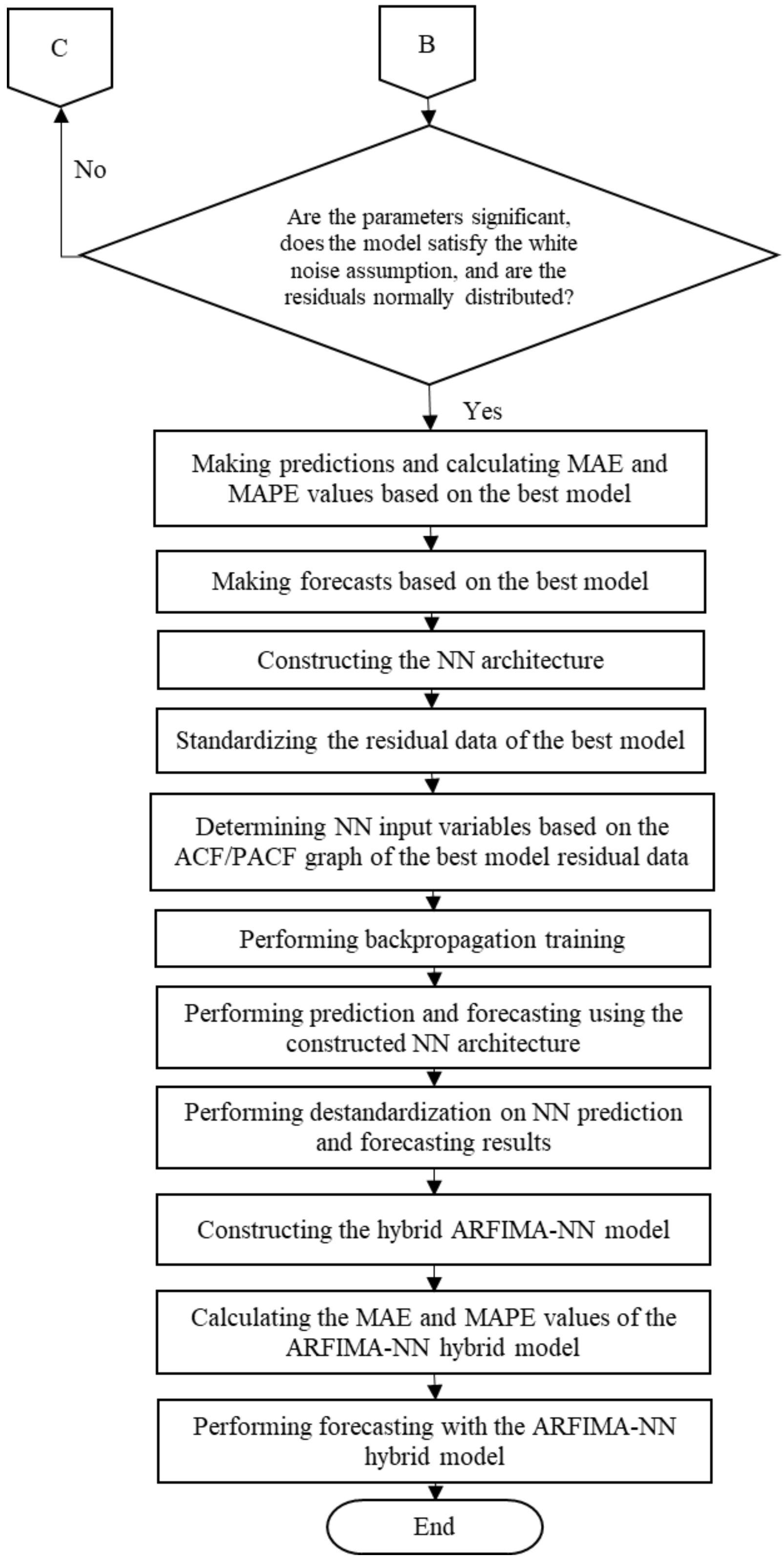


Figure 1. Research Flowchart

4. Result and Discussion

4.1. Description of Closing Price Data for the Jakarta Composite Index

Table 1. Descriptive Statistics

n	Min	Max	Mean	Standard Deviation
240	1,029.61	7,670.73	4,501.84	1,925.31

Table 1 presents the descriptive statistics summary for the Jakarta Composite Index (JCI) closing prices over the 2005–2024 period, consisting of 240 observations. The mean JCI value is recorded at 4,501.84, with values ranging from a minimum of 1,029.61 to a maximum of 7,670.73 and a standard deviation of 1.925.31.

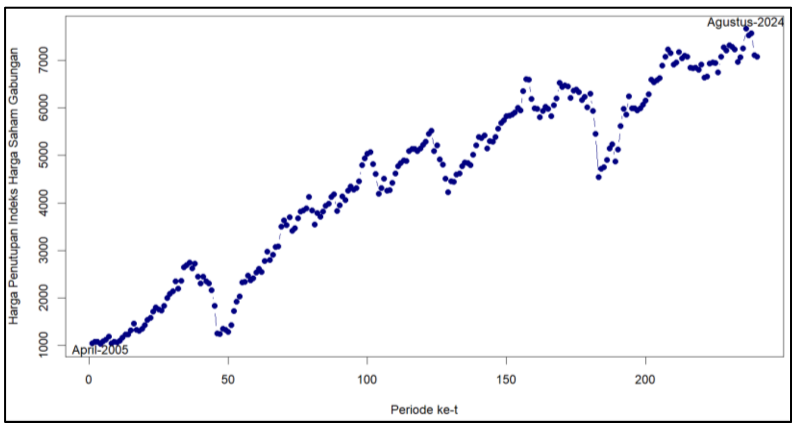


Figure 2. Time series graph of JCI closing price data

Figure 2 demonstrates that the closing price data of the JCI for the period January 2005 to December 2024 shows an upward trend pattern. In April 2005, the JCI reached its lowest point in April at 1,029.61. Meanwhile, the highest JCI occurred in August 2024 at 7,670.73.

4.2. ACF Graph

After performing descriptive statistics, the ACF graph is shown in Figure 3.

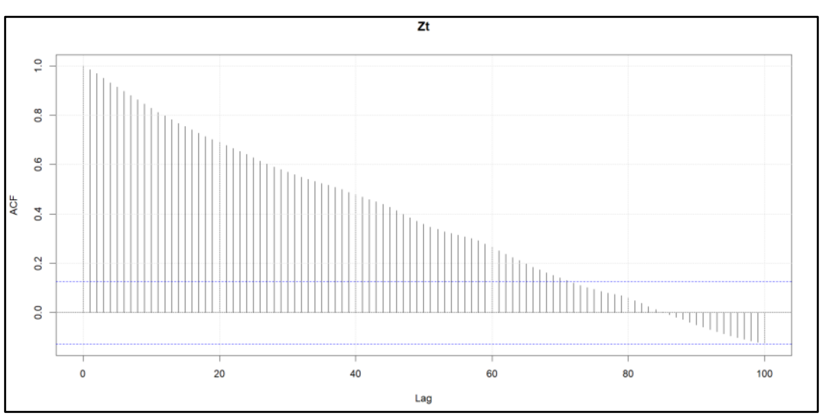


Figure 3. ACF graph of JCI closing price data

Based on Figure 3, the ACF graph visually shows that the ACF graph decreases slowly or hyperbolically, an initial indication of a long memory effect in the data. However, visual observation is still subjective. To confirm the existence of a long memory pattern, a Rescaled Range Statistics (R/S) statistical analysis was performed, which produced a Hurst (H) value of 0.81. Given that this value meets the criteria of $0.5 < H < 1$, this proves that the JCI closing price data has long memory properties.

4.3. Data Stationary Test

Figure 2 demonstrates that the series has not yet achieved variance stationarity. The Box-Cox transformation test results show an estimated value of 1.097553. Although the value is close to 1, suggesting that the variance of the data has achieved stationarity, the power transformation is still carried out to optimize forecasting accuracy, which is raised to the power of 1.097553.

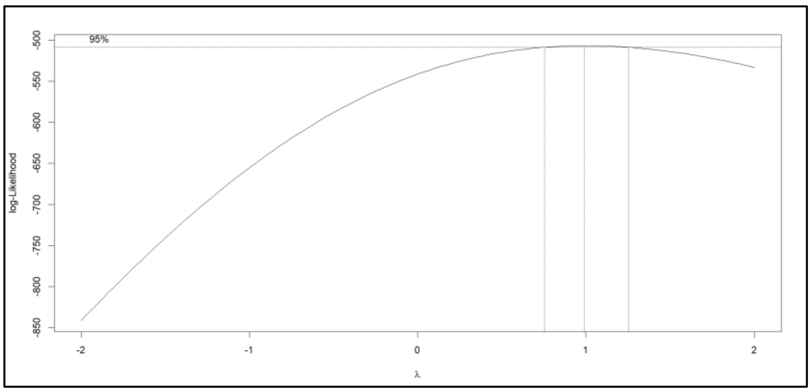


Figure 4. λ value graph for JCI closing price data after transformation

Based on the results of the Box-Cox transformation in Figure 4, the estimated value of the parameter λ is 1. This indicates that the data has achieved stationarity in variance, therefore, no further transformation is required. The time series graph after the transformation stage is shown in Figure 5.

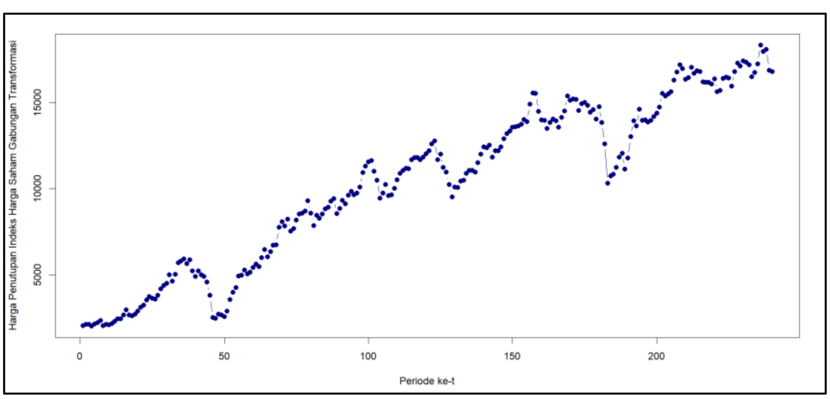


Figure 5. Time series graph of JCI closing price data after transformation

After examining the stationarity of the data in variance, the next step is to test the stationarity of the mean. Visually, the time series graph in Figure 5 shows that the data is not stationary in terms of the mean because it still has a trend. This is reinforced by the ADF test results, which conclude that the transformed data does not meet the criteria for mean stationarity. To overcome this condition, a differencing process is required. Because the initial data indicated a long memory pattern, the differencing process was carried out by calculating the differencing order (D) value, which is a fractional number. The GPH method yielded a fractional differencing order (D) of 0.51. The resulting time series graph, following the differencing process, is illustrated in Figure 6.

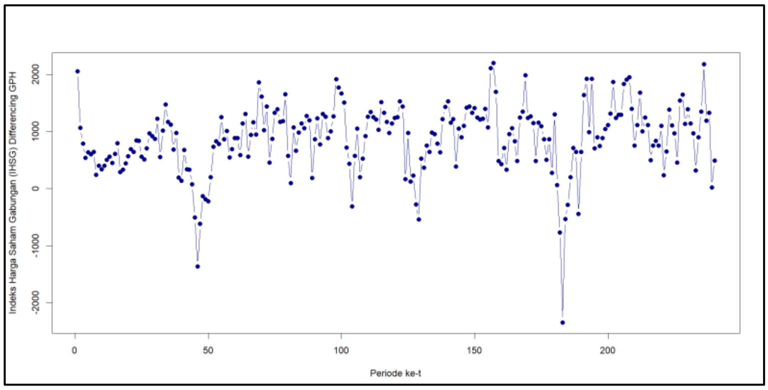
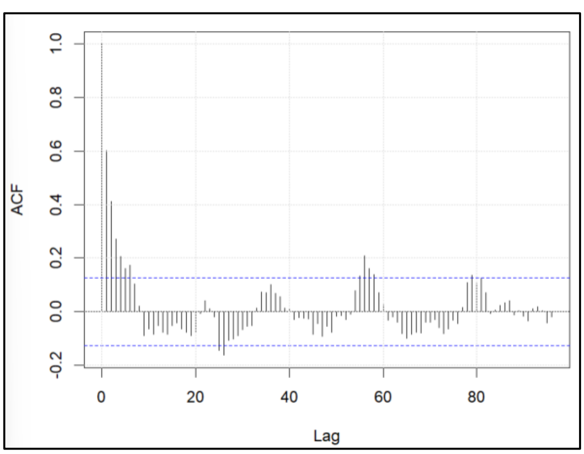


Figure 6. Time series graph of data differencing using the GPH method

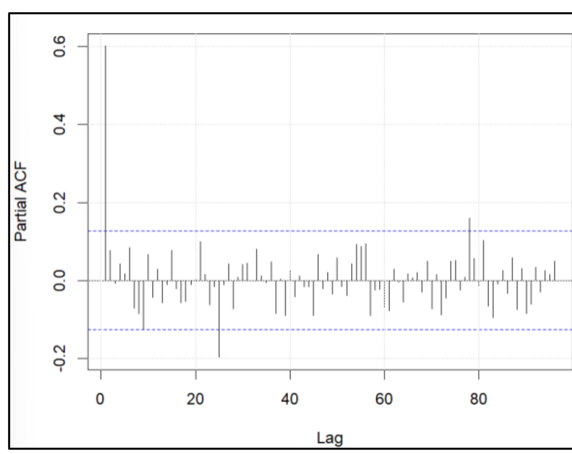
Based on Figure 6 and reinforced by the results of the ADF statistical test, this indicates that the differencing data has achieved stationarity in the mean.

4.4. Identification of Tentative ARFIMA Model

The ACF and PACF graphs are shown in Figure 7.



(a) ACF graph



(b) PACF graph

Figure 7. ACF and PACF graphs (0,51) GPH

Based on Figure 7(a), the ACF graph shows a cut-off pattern after lag 6, but the lag used is limited to lag 4 using the principle of parsimony. Meanwhile, based on Figure 7(b), the PACF graph shows a cut-off after lag 1.Therefore, the resulting tentative ARFIMA models are shown in Table 2.

Table 2. Equations of the Tentative ARFIMA Models

Model	Model Equation
ARFIMA (0;0.51;1)	$(1-B)^{0.51}Z_t=(1-\theta_1 B)e_t$
ARFIMA (0;0.51;2)	$(1-B)^{0.51}Z_t=(1-\theta_1 B-\theta_2 B^2)e_t$
ARFIMA (0;0.51;3)	$(1-B)^{0.51}Z_t=(1-\theta_1 B-\theta_2 B^2-\theta_3 B^3)e_t$
ARFIMA (0;0.51;4)	$(1-B)^{0.51}Z_t=(1-\theta_1 B-\theta_2 B^2-\theta_3 B^3-\theta_4 B^4)e_t$
ARFIMA (1;0.51;0)	$(1-\phi_1 B)(1-B)^{0.51}Z_t=e_t$
ARFIMA (1;0.51;1)	$(1-\phi_1 B)(1-B)^{0.51}Z_t=(1-\theta_1 B)e_t$
ARFIMA (1;0.51;2)	$(1-\phi_1 B)(1-B)^{0.51}Z_t=(1-\theta_1 B-\theta_2 B^2)e_t$
ARFIMA (1;0.51;3)	$(1-\phi_1 B)(1-B)^{0.51}Z_t=(1-\theta_1 B-\theta_2 B^2-\theta_3 B^3)e_t$
ARFIMA (1;0.51;4)	$(1-\phi_1 B)(1-B)^{0.51}Z_t=(1-\theta_1 B-\theta_2 B^2-\theta_3 B^3-\theta_4 B^4)e_t$

4.5. Parameter Estimation and Significance Testing

The next step is estimation followed by a significance test of the parameters in the tentative ARFIMA model, which are detailed in Table 3.

Table 3. Estimation and Significance Testing of ARFIMA Model Parameters

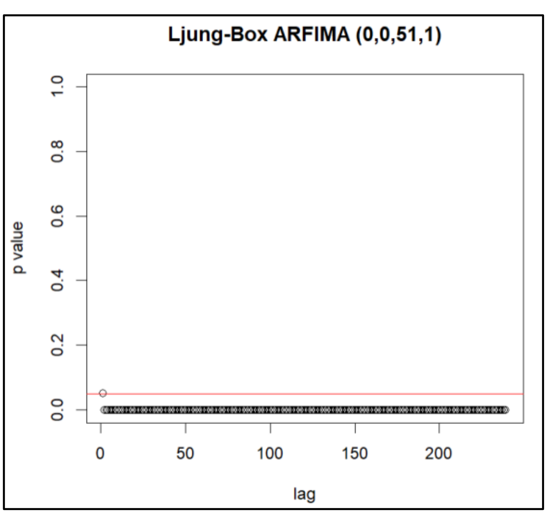
Model	Estimation Parameter	$t_{statistic}$	*db*	$t_{0,025;db}$	*p-value*	Decision
ARFIMA (0;0.51;1)	$\hat{\theta}_1=0.66$	19.03	239	1.96	$<2.2\times10^{-16}$	H_0 is rejected
ARFIMA (0;0.51;2)	$\hat{\theta}_1=0.85$	14.62	238	1.96	$<2.2\times10^{-16}$	H_0 is rejected
	$\hat{\theta}_2=0.50$	10.71			$<2.2\times10^{-16}$	H_0 is rejected
ARFIMA (0;0.51;3)	$\hat{\theta}_1=0.81$	11.53	237	1.97	$<2.2\times10^{-16}$	H_0 is rejected
	$\hat{\theta}_2=0.64$	11.68			$<2.2\times10^{-16}$	H_0 is rejected
	$\hat{\theta}_3=0.34$	6.19			6.14×10^{-9}	H_0 is rejected
ARFIMA (0;0.51;4)	$\hat{\theta}_1=0.84$	13.76	236	1.97	$<2.2\times10^{-16}$	H_0 is rejected
	$\hat{\theta}_2=0.79$	11.27			$<2.2\times10^{-16}$	H_0 is rejected
	$\hat{\theta}_3=0.61$	8.47			$<2.2\times10^{-16}$	H_0 is rejected
	$\hat{\theta}_4=0.34$	6.31			2.63×10^{-10}	H_0 is rejected
ARFIMA (1;0.51;0)	$\hat{\phi}_1=0.88$	29.77	239	1.96	$<2.2\times10^{-16}$	H_0 is rejected
ARFIMA	$\hat{\phi}_1=0.95$	39.28	238	1.96	$<2.2\times10^{-16}$	H_0 is rejected

(1;0.51;1)	$\hat{\theta}_1 = -0.30$	-3.51			4.44×10^{-4}	H_0 is rejected
ARFIMA (1;0.51;2)	$\hat{\phi}_1 = 0.97$	50.04	237	1.97	$< 2.2 \times 10^{-16}$	H_0 is rejected
	$\hat{\theta}_1 = -0.33$	-4.65			3.33×10^{-6}	H_0 is rejected
	$\hat{\theta}_2 = -0.15$	-2.00			0.045	H_0 is rejected
ARFIMA (1;0.51;3)	$\hat{\phi}_1 = 0.98$	67.25	236	1.97	$< 2.2 \times 10^{-16}$	H_0 is rejected
	$\hat{\theta}_1 = -0.35$	-4.93			8.06×10^{-7}	H_0 is rejected
	$\hat{\theta}_2 = -0.14$	-1.80			0.0733	Fail to reject H_0
	$\hat{\theta}_3 = -0.15$	-2.03			0.0420	H_0 is rejected
ARFIMA (1;0.51;4)	$\hat{\phi}_1 = 0.99$	1982.27	235	1.97	$< 2.2 \times 10^{-16}$	H_0 is rejected
	$\hat{\theta}_1 = -0.42$	-6.42			1.32×10^{-10}	H_0 is rejected
	$\hat{\theta}_2 = -0.17$	-2.52			0.011520	H_0 is rejected
	$\hat{\theta}_3 = -0.20$	-3.01			0.002587	H_0 is rejected
	$\hat{\theta}_4 = -0.17$	-2.65			0.007935	H_0 is rejected

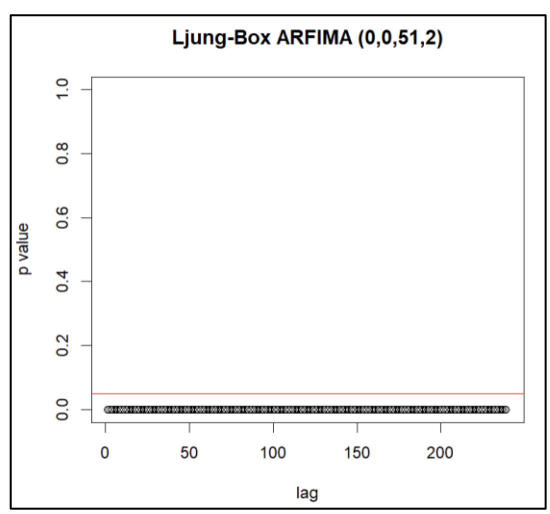
The results presented in Table 3 indicate that several tentative ARFIMA models possess significant parameters, specifically the ARFIMA (0;0.51;1), ARFIMA (0;0.51;2), ARFIMA (0;0.51;3), ARFIMA (0;0.51;4), ARFIMA (1;0.51;0), ARFIMA (1;0.51;1), ARFIMA (1;0.51;2), dan ARFIMA (1;0.51;4).

4.6. ARFIMA Diagnostic Model

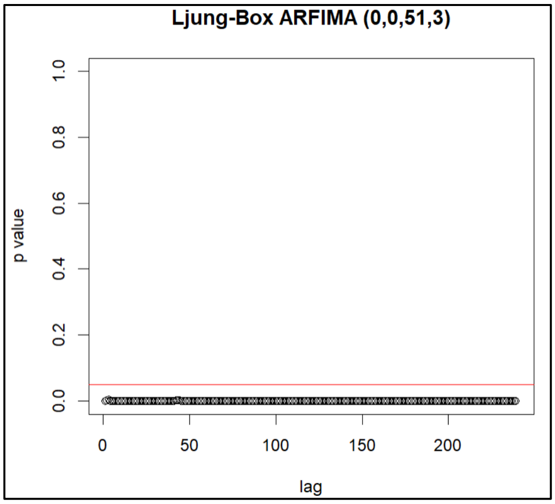
The first stage in the diagnostic examination is to test the assumption of white noise residuals. The p-values of the ARFIMA model and the results of the Ljung-Box test are shown in Figure 8.



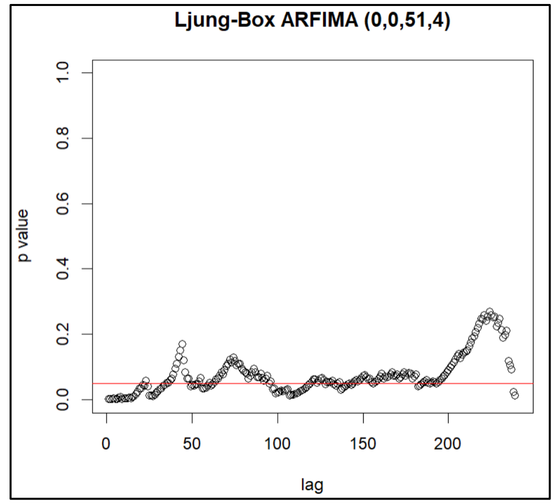
(a) ARFIMA (0;0.51;1)



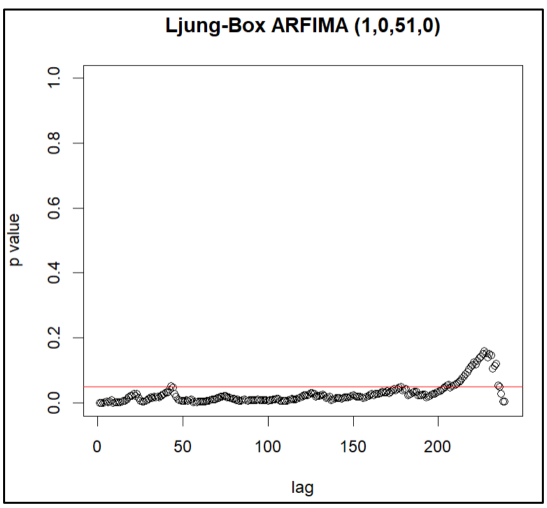
(b) ARFIMA (0; 0.51;2)



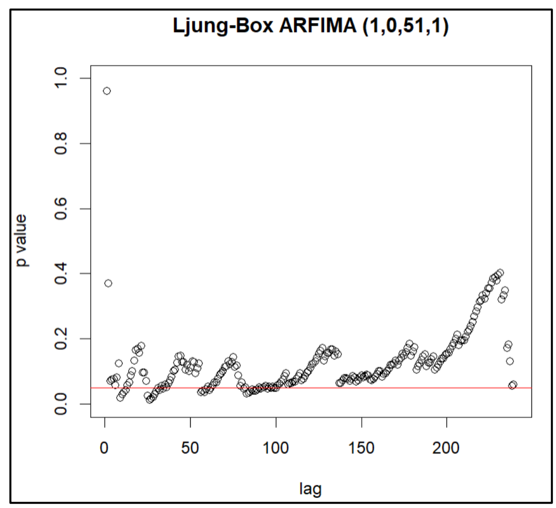
(c) ARFIMA (0; 0.51;3)



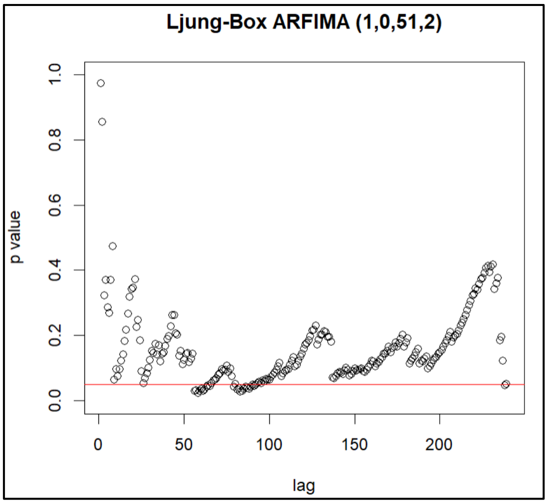
(d) ARFIMA (0; 0.51;4)



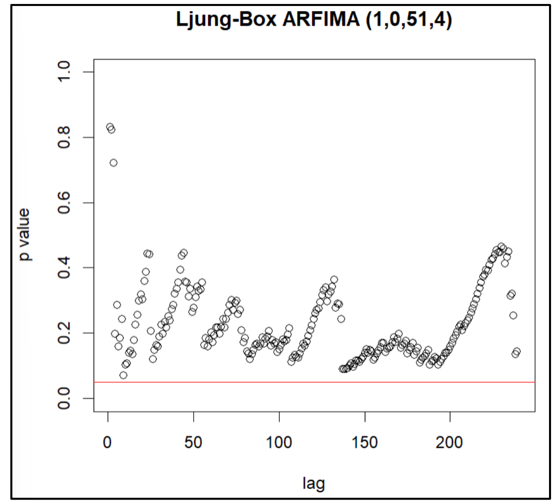
(e) ARFIMA (1; 0.51;0)



(f) ARFIMA (1; 0.51;1)



(g) ARFIMA (1; 0.51;2)



(h) ARFIMA (1; 0.51;4)

Figure 8. Ljung-box ARFIMA testing graph

Figure 8 demonstrates that the white noise assumption is not fulfilled in Figures 8(a) to 8(g) because there are p-values below the significance line. Following the diagnostic results in Figure 8(h), which confirm that the ARFIMA (1; 0.51; 4) residuals fulfillment of the white noise assumption. To further validate the model, a Kolmogorov-Smirnov test was conducted to examine residual normality with the results detailed in Table 4.

Table 4. Residual Normality Test

Model	$D_{statistic}$	$D_{(0,05,240)}$	*p-value*	Decision
ARFIMA (1;0,51;4)	0,07	0,09	0,1805	Fail to reject H_0

According to the test results presented in Table 4, the statistical decision indicates that is to fail to reject H_0, leading to the conclusion that the ARFIMA (1;0.51;4) model residuals are normally distributed. Following the significance tests and the series of diagnostic checks conducted, the ARFIMA (1;0.51;4) model is established as the best model, as it satisfies all the required assumptions.

4.7. Best ARFIMA Model

The closing price prediction of the JCI based on the ARFIMA (1;0.51;4) model for the period January 2005 to December 2024 is shown in Table 5.

Table 5. JCI Prediction for the period January 2005 to December 2024

Period	**Month**	**Actual Data (Z_t)**	**Prediction Result ($\hat{Z}_t$)**
1	January 2005	1,045.43	609.08
2	February 2005	1,073.83	1,163.93
⋮	⋮	⋮	⋮
240	December 2024	7,079.90	7,188.53

After obtaining the prediction results in Table 5, they were then used as a basis for determining the MAE and MAPE values. The calculation results show that the MAE value obtained was 262.36 and the MAPE was 7.85%. Where the MAPE value is below 10%, it means that the ARFIMA (1;0.51;4) model has a very good forecasting ability.

4.8. ARFIMA Forecasting

The JCI forecast based on the ARFIMA (1;0.51;4) model for the next 12 periods, from January 2025 to December 2025, is shown in Table 6.

Table 6. JCI forecast for the period January 2025 to December 2025

Period	Month	Forecast Result
241	January 2025	6,932.73
242	February 2025	6,962.52
243	March 2025	7,028.01
244	April 2025	7,052.74
245	May 2025	7,073.76
246	June 2025	7,092.41
247	July 2025	7,109.72
248	August 2025	7,126.24
249	September 2025	7,142.25
250	October 2025	7,157.91
251	November 2025	7,173.31
252	December 2025	7,188.53

4.9. Hybrid ARFIMA-NN

The NN method with the backpropagation algorithm requires data standardization first to adjust to the activation function implemented in this model, namely the binary sigmoid function. The standardization used in this study is min-max standardization, where the newmax value used is 0.9 and the newmin value is 0.1. After standardizing the ARFIMA (1;0.51;4) model residual data, the next step is to determine the input variables in the NN. It can be seen that in the ACF graph there are 35 significant lags and in the PACF graph there are 7 significant lags. The determination of the input variables used is based on the PACF graph using the principle of parsimony. The determination of input variables will be based on a combination of significant PACF values and the smallest MAPE value. Based on trial and error, the smallest MAPE value obtained is 18.24%, so the input variables (x_A) used are at lag 1 (e^*_{t-1}) as x_1 and at lag 3 (e^*_{t-3}) as x_2.

Then, data standardization and input variable determination were carried out, followed by the backpropagation stage. The backpropagation stage was carried out by determining the number of neurons in the hidden layer. In this study, 1 to 3 neurons were used. The training process was carried out with a learning rate of 0.001 and would stop when the target error reached 0.05 and a maximum of 10,000 iterations. The best hybrid ARFIMA-NN model was selected using MAE and MAPE values. The MAE and MAPE calculation results for 1, 2, and 3 hidden layer neurons are shown in Table 7.

Table 7. Accuracy Calculation Results on the ARFIMA-NN Hybrid Model

Number of Neurons in the Hidden Layer	MAPE	MAE
1 Neuron	7.68%	262.84
2 Neuron	7.68%	262.83
3 Neuron	7.69%	262.84

Based on Table 7, it can be seen that the smallest MAE and MAPE values are found in the 2-neuron ARFIMA-NN hybrid.

4.10. ARFIMA-NN Hybrid Prediction and Forecasting

The NN architecture consisting of 2 hidden layer neurons is shown in Figure 9.

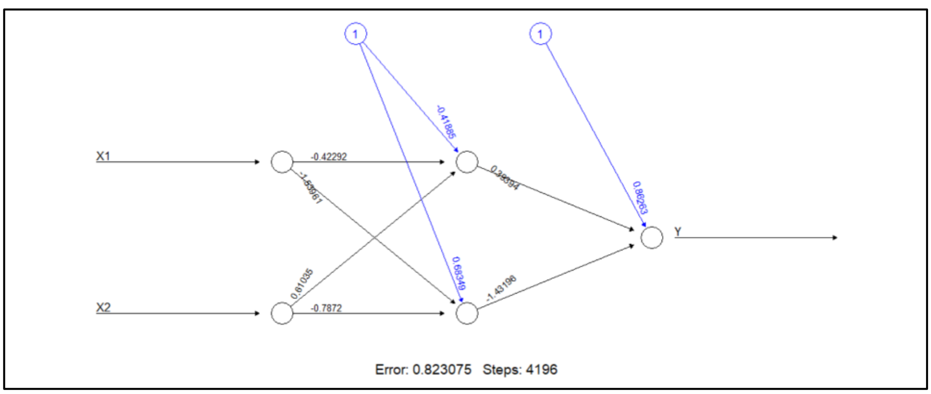


Figure 9. Backpropagation network architecture with 2 hidden layers

The optimal weight and residual values for 2 neurons in the hidden layer based on the ARFIMA residual (1;0.51;4)

$$\mathbf{w} = \begin{bmatrix} w_{01} & w_{02} \\ w_{11} & w_{12} \\ w_{21} & w_{22} \end{bmatrix} = \begin{bmatrix} -0.42 & 0.68 \\ -0.428 & -1.54 \\ 0.61 & -0.79 \end{bmatrix}.$$

$$\mathbf{v} = \begin{bmatrix} v_{01} \\ v_{11} \\ v_{21} \end{bmatrix} = \begin{bmatrix} 0.86 \\ 0.40 \\ -1.43 \end{bmatrix}.$$

The Hybrid ARFIMA (1;0.51;4)-NN 2 Neuron model can be systematically written as follows:

$$\hat{H}_t = 1.50Z_{t-1} - 0.38Z_{t-2} - 0.06Z_{t-3} - \ldots + e_t + 0.42e_{t-1} + 0.17e_{t-2} + 0.20e_{t-3} + 0.17e_{t-4} + \hat{N}_{2,t}$$

The results of the JCI closing price prediction for the period January 2005 to December 2024 using the ARFIMA(1;0.51;4)-NN hybrid model with 2 layers of hidden neurons are shown in Table 8.

Table 8. JCI Closing Price Prediction Results Using the Hybrid ARFIMA (1;0.51;4)-NN 2 Neuron Model

t	Actual Data	ARFIMA	NN 2 Neuron	*Hybrid* ARFIMA-NN 2 Neuron
4	1,029.61	1,200.82	0.35	1,201.17
5	1,088.17	1,195.09	0.40	1,1195.49
⋮	⋮	⋮	⋮	⋮
240	7,079.90	6,936.91	0.36	6,937.27

The ARFIMA-NN hybrid model forecast is calculated in the same way as the prediction calculation. The number of forecasts made is for the next 12 periods, from January 2025 to December 2025. The forecast results using the 2-neuron ARFIMA-NN model are shown in Table 9.

Table 9. JCI Closing Price Forecast Results Using the Hybrid ARFIMA (1;0.51;4)-NN 2 Neuron Model

Period	Month	Forecast Result
241	January 2025	6,933.05
242	February 2025	6,962.88
243	March 2025	7,028.36
244	April 2025	7,053.08
245	May 2025	7,074.11
246	June 2025	7,092.76
247	July 2025	7,110.07
248	August 2025	7,126.59
249	September 2025	7,142.60
250	October 2025	7,158.26
251	November 2025	7,173.66
252	December 2025	7,188.88

The results of forecasting using the ARFIMA-NN model with 2 neurons compared to actual data are shown in Figure 10.

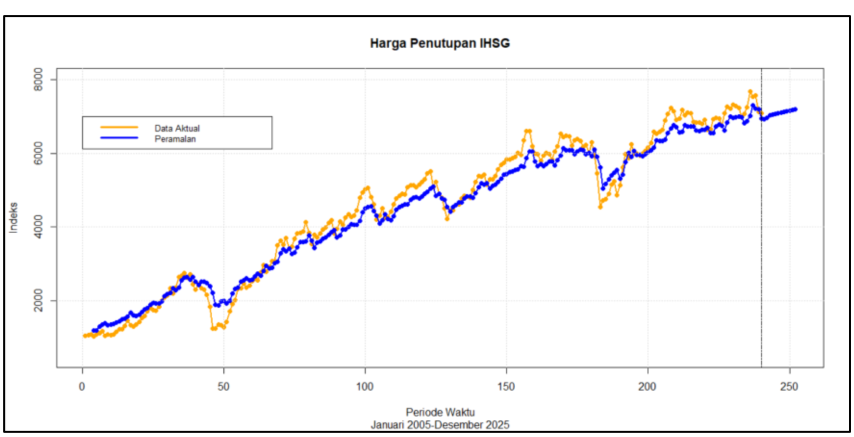


Figure 10. Hybrid ARFIMA-NN Model with 2 Neurons

Based on Figure 10, it can be seen that the prediction results using 2 hidden layer neurons have a data pattern that is close to the actual data. Furthermore, the graph of the forecast results for the period January to December 2025 also shows an upward and fluctuating pattern.

5. Conclusion

Based on the analysis of the closing price of the JCI from January 2005 to December 2024, three hybrid models were identified. The ARFIMA-NN Hybrid Model with 2 neurons was identified as the best model, producing the lowest accuracy with an MAE of 262.83 and a MAPE of 7.68%. The implementation of the ARFIMA model in this study was specifically designed to address the long-memory characteristics of the JCI data that could not be captured by ARIMA, while the integration of Neural Network (NN) aimed to model non-linear patterns in the residuals to improve forecasting accuracy. The forecasting results for the period January to December 2025 show that the JCI closing price is predicted to experience a fluctuating but generally increasing trend. With a MAPE value below 10%, this hybrid model is categorized as having excellent forecasting capabilities, thereby providing practical contributions to investors in mitigating capital market volatility risks.

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