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Forecasting Indonesian Nickel Reference Mineral Prices Using a Hybrid Intervention-Neural Network Model

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Keywords: step function, Indonesian Nickel Price, Hybrid Model, Intervention Analysis, Neural Network.

Abstract:

Time series data influenced by external events often exhibit abrupt changes and nonlinear patterns, making them difficult to model using a single forecasting approach. Hybrid models have emerged as an alternative by combining the strengths of linear and nonlinear models to improve forecasting accuracy. One approach that can be applied is the hybrid Intervention–Neural Network (NN) model. This study aims to obtain the best hybrid Intervention–NN model for forecasting Indonesian Nickel Reference Mineral Prices (Harga Mineral Acuan/HMA) using monthly data from January 2018 to February 2025, which were affected by the Russia–Ukraine conflict in February 2022. Modeling was conducted using intervention analysis with a *step function* combined with NN models consisting of 1, 2, 3, and 4 hidden neurons. The results indicate that the optimal model is the hybrid intervention ARIMA(1,1,0) *step function* model combined with a two-neuron NN, yielding an RMSE value of 1,074.3652 and a MAPE value of 4.7735%. Forecasts for the period from March 2025 to February 2026 indicate a downward trend in nickel prices.

1. Introduction

Time series analysis, as a statistical technique, focuses on identifying patterns in historical data as the basis for forecasting. Among various forecasting approaches, the *Autoregressive Integrated Moving Average* (ARIMA) model is one of the most widely applied methods. ARIMA models are considered effective for modeling linear and stationary data; however, they have significant limitations when extreme fluctuations or structural changes occur as a result of certain events. Events beyond the control of the observed system that affect the data structure are referred to as interventions (Wei, 2006). Intervention analysis, using either *step* or *pulse functions*, is commonly employed to describe the impact of external events on time series data. Nevertheless, intervention models are not always able to adequately capture complex nonlinear patterns.

One method that is flexible in identifying nonlinear patterns is the *Neural Network* (NN) model (Kusumaningrum et al., 2023). Neural Networks have demonstrated strong forecasting capabilities in modeling nonlinear relationships (Wahyuni et al., 2023). Zhang (2003) stated that no single method is capable of capturing both linear and nonlinear patterns simultaneously. Therefore, hybrid approaches combining two or more methods have been developed, one of which is the hybrid Intervention-NN model. The hybrid Intervention–NN model first captures the effects of special

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events using intervention analysis and subsequently models the residuals using NN to capture the remaining nonlinear patterns.

This approach is particularly relevant for nickel commodities, which are highly volatile and strongly influenced by global dynamics. Indonesia, as one of the world's largest nickel producers, contributed nearly 50% of global nickel production during 2022-2023 (Carista, 2025). However, nickel price stability is highly sensitive to geopolitical factors. The Russia–Ukraine conflict that began on February 24, 2022, disrupted global supply chains and caused nickel prices to surge by approximately 250% (Natalia & Hutabarat, 2025). As a result, Indonesian nickel HMA increased sharply and reached its peak in April 2022 at 35,995.30 USD/dmt (Ditjen Minerba, 2025). This phenomenon indicates the presence of an intervention effect on nickel price movements. The phenomenon also highlights the importance of forecasting Indonesian Nickel Reference Mineral Prices, considering Indonesia's strategic position in the global nickel market. Forecasting HMA prices can provide valuable information for policymakers and industry stakeholders in making decisions related to production, investment, and mineral trade.

Previous studies have shown that intervention models and hybrid models can improve forecasting accuracy, such as in studies of tourist arrivals (Ramadhani et al., 2022), inflation forecasting (Masrawanti et al., 2019), and various hybrid NN models with high predictive performance, indicating that hybrid NN models generally outperform single models (Kusumaningrum et al., 2023; Wahyuni et al., 2023; Saluza et al., 2022). For nickel commodities, hybrid approaches have also demonstrated good performance (Carista et al., 2025). Consistent with these findings, this study applies a combination of intervention analysis and NN to forecast Indonesian nickel HMA by incorporating the Russia-Ukraine conflict as an intervention factor in the modeling process.

Considering this background, this study aims to obtain the best hybrid Intervention-NN model for forecasting Indonesian nickel HMA by incorporating the impact of the Russia-Ukraine conflict that began in February 2022, which caused a surge in global nickel prices and affected prices in Indonesia.

2. Literature Review

2.1 Intervention Analysis

According to Suhartono (2007), an intervention model is an approach in time series analysis used to examine the effects of unexpected external events on observed data. The general form of the intervention model can be expressed in Equation (1).

$$Z_t = f(\beta, I_t) + e_t \tag{1}$$

where e_t represents the noise model (the ARIMA model before intervention), which is expressed in Equation (2).

$$\phi_p(B)(1-B)^d Z_t = \theta_q(B) a_t \tag{2}$$

The intervention response is defined as follows.

$$f(\beta, I_t) = \frac{\omega_s(B)}{\delta_r(B)} B^b I_t \tag{3}$$

Intervention variables are classified into two categories, namely step and pulse functions. An intervention with a long-term impact is represented by a step function (Suhartono, 2007). When an event is categorized as a step function, its effect is considered permanent or persists over a relatively long period in the observed data (Montgomery et al., 2008), and its mathematical representation is given in Equation (4).

$$I_t^{(T)} = S_t^{(T)} = \begin{cases} 0, & t < T \\ 1, & t \geq T \end{cases} \tag{4}$$

where T denotes the time at which the intervention begins.

According to Wei (2006), the response to an intervention can be identified by observing the overall data plot to detect changes in patterns occurring after the intervention. Furthermore, the response can be identified by determining the orders b, s, and r, which are essential components in intervention modeling. The order $b$represents the delay before the intervention effect first appears, the order $s$indicates the duration of the intervention effect until the data return to stability, and the order $r$reflects the pattern that develops after the effects represented by $b$and s. These orders are determined based on the residual plot of the ARIMA model fitted to the pre-intervention data using significance limits of ±3× RMSE.

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(Z_t - \hat{Z}_t\right)^2} \tag{5}$$

2.2 Neural Network

A Neural Network (NN) is a data processing method that mimics the working principles of the human nervous system in identifying patterns (Fausett, 1994). An NN consists of interconnected neurons that operate simultaneously to process information and solve problems (Primartha, 2018). These connections are adaptive, meaning that the network is capable of adjusting itself and learning new information through a learning process.

The NN framework is characterized by the number of layers and the number of neurons within each layer. In general, an NN consists of three layers: an input layer, a hidden layer, and an output layer. The input layer receives input data, the hidden layer performs internal information processing that cannot be directly observed, and the output layer generates the final output of the learning process (Puspitaningrum, 2006). According to Fausett (1994), the architecture of an NN refers to the arrangement of neurons within layers and the pattern of connections both within and between these layers.

In this study, the NN component employed a Feedforward Neural Network (FFNN) architecture trained using the backpropagation algorithm. The network consisted of an input layer, a single hidden layer, and an output layer. To determine the optimal model, the number of neurons in the hidden layer was varied to include 1, 2, 3, and 4 neurons.

2.3 Hybrid Intervensi-NN

The hybrid Intervention-NN model combines intervention analysis and NN modeling to improve forecasting accuracy and reduce the risk of model misspecification. This hybrid approach is also capable of capturing both linear and nonlinear patterns in time series data, considering that most real-world data are neither purely linear nor purely nonlinear (Wahyuni et al., 2023).

According to Zhang (2003) in Wahidah et al. (2024), the hybrid Intervention-NN model generally combines an intervention model with an NN model, where the residuals from the intervention model are used as inputs to the NN in order to capture nonlinear patterns that cannot be accommodated by the intervention model alone. The final hybrid forecasts are obtained by combining the forecasts from the intervention model and the NN forecasts of the residuals.

$$\hat{H}_t = \hat{Z}_t + \hat{N}_t \tag{6}$$

2.4 Ukuran Ketepatan Peramalan

According to Aswi and Sukarna (2006), when several candidate models satisfy parameter significance and diagnostic tests, specific criteria are required to determine the optimal model. The selection process is based on forecasting errors, where the model with the smallest error is considered the best-performing model. In this study, model evaluation and selection were conducted using the *Root Mean Square Error* (RMSE), as presented in Equation (5), and the *Mean Absolute Percentage Error* (MAPE), as defined in Equation (7).

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Z_t - \hat{Z}_t}{Z_t}\right| \times 100\% \tag{7}$$

The levels of forecasting accuracy based on MAPE values are presented in Table 1.

Tabel 1. MAPE Accuracy Criteria

MAPE Value	Accuracy Criteria
MAPE $\leq$ 10%	Highly accurate forecasting model
10% < MAPE $\leq$ 20%	Accurate forecasting model
20% < MAPE $\leq$ 50%	Reasonably accurate forecasting model
MAPE > 50%	Inaccurate forecasting model

Sumber :Hudiyanti (2019).

2.5 Harga Mineral Acuan Nikel

Nickel is a strategic metal widely used in the electric vehicle battery industry and stainless-steel production. The increasing demand for environmentally friendly energy has caused the demand for and prices of nickel worldwide, including in Indonesia, to become highly volatile (Aprisal & Abadi, 2019). Indonesia has been the world's largest nickel producer since 2019 and has made a significant contribution to the global nickel market (Carista et al., 2025).

In Indonesia, the official price used in mineral trading is referred to as the Reference Mineral Price (Harga Mineral Acuan, HMA), which is determined by the Ministry of Energy and Mineral Resources (Kementerian Energi dan Sumber Daya Mineral, ESDM) as the benchmark price for metal mineral transactions (Ditjen Minerba, 2025). Despite increasing production, nickel prices remain highly sensitive to geopolitical factors. The Russia-Ukraine conflict in February 2022 disrupted global supply chains and triggered a price surge of approximately 250% (Natalia & Hutabarat, 2025), causing Indonesian nickel HMA to reach its highest level during the observation period in April 2022 at 35,995.30 USD/dmt (Ditjen Minerba, 2025).

3. Research Methodology

The data used in this study consisted of Indonesian Nickel Reference Mineral Prices (HMA) from January 2018 to February 2025 obtained from the official website of the Ministry of Energy and Mineral Resources of the Republic of Indonesia (minerba.esdm.go.id), based on data availability and recency. The intervention variable considered in this study was the impact of the Russia-Ukraine conflict, which began in February 2022. With the assistance of RStudio, SAS, and Microsoft Excel software, the data analysis procedures were conducted as follows.

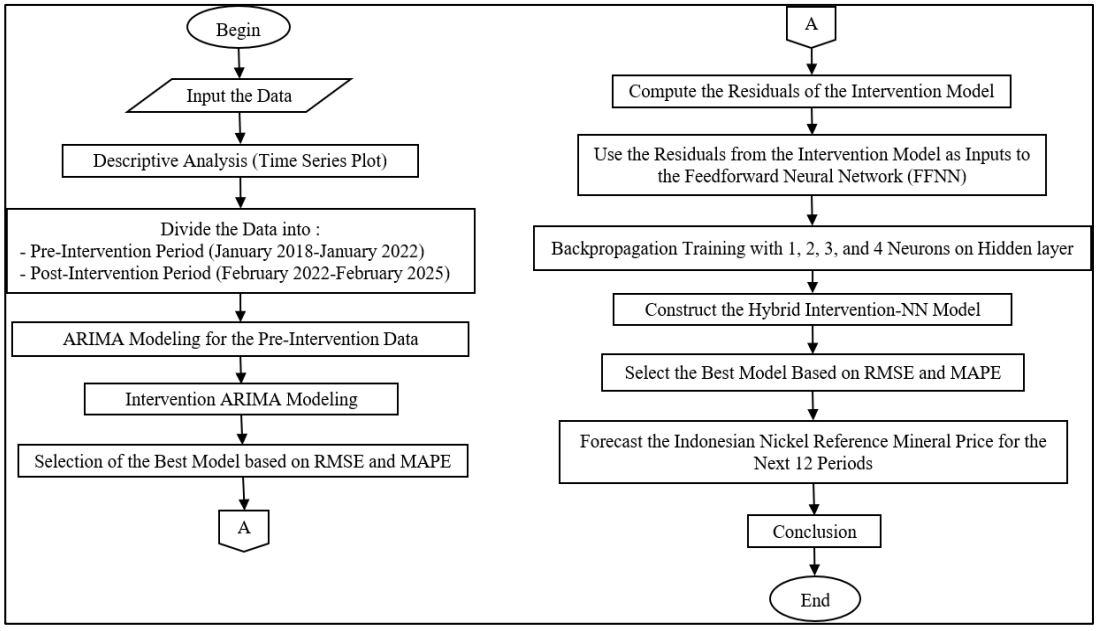


Figure 1. Research Flowchart

4. Results and Discussion

4.1. Descriptive Analysis of Indonesian Nickel Reference Mineral Price Data

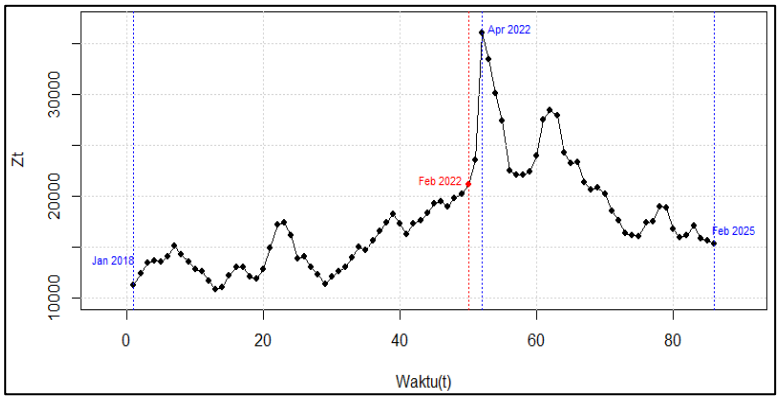


Figure 2. Time Series Plot of Indonesian Nickel Reference Mineral Prices

Based on Figure 2, Indonesian nickel HMA from January 2018 to early 2022 fluctuated with an increasing trend. In February 2022, coinciding with the Russia-Ukraine conflict, a significant increase occurred and reached its peak in April 2022, representing the highest value during the observation period. Subsequently, the prices gradually declined until February 2025. The difference in patterns before and after February 2022 indicates the presence of a significant intervention effect; therefore, intervention analysis is required to model the data.

4.2. Data Partitioning

The initial stage of intervention modeling involved dividing the data into two groups based on the timing of the intervention event. The first group consisted of the pre-intervention period, namely January 2018 to January 2022, during which Indonesian nickel HMA had not yet been affected by the Russia-Ukraine conflict. The second group consisted of the post-intervention period, namely February 2022 to February 2025, with February 2022 defined as the intervention point since it marked the beginning of the Russia-Ukraine conflict.

4.3. ARIMA Modeling for Pre-Intervention Data

Prior to incorporating the intervention effect, modeling was performed on the first data group using the ARIMA approach. The analysis process consisted of several stages, including stationarity testing, model identification, parameter estimation, parameter significance testing, diagnostic checking, and forecasting.

Based on Figure 2, the pre-intervention Indonesian nickel HMA data were suspected to be non-stationary in both variance and mean. The results of the Box-Cox transformation showed that the estimated value of λ before transformation was 1.103547, indicating that the data were non-stationary in variance because the value was considerably different from 1. Therefore, a power transformation was applied to the Indonesian nickel HMA data. After the transformation, the estimated value became 1, indicating that the variance had become stable.

Subsequently, stationarity in mean was evaluated using the ACF plot and the Augmented Dickey-Fuller (ADF) test.

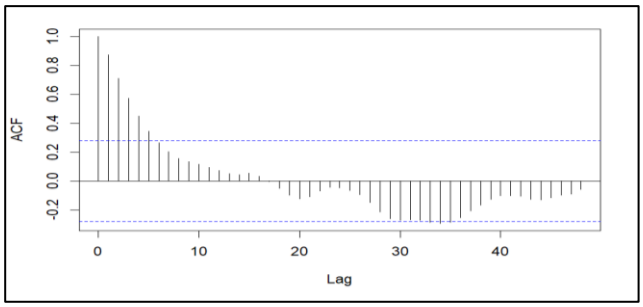


Figure 3. ACF Plot of the First Data Group

Based on Figure 3, the gradually declining ACF pattern indicates that the data were non-stationary in mean. The results of the Augmented Dickey-Fuller (ADF) test at a 5% significance level produced a p-value of 0.7539, which was greater than 0.05, indicating that the data were non-stationary in mean. Therefore, first-order differencing was applied to achieve stationarity. After the differencing process, the data were re-evaluated for stationarity. The results after differencing are presented in Figure 4.

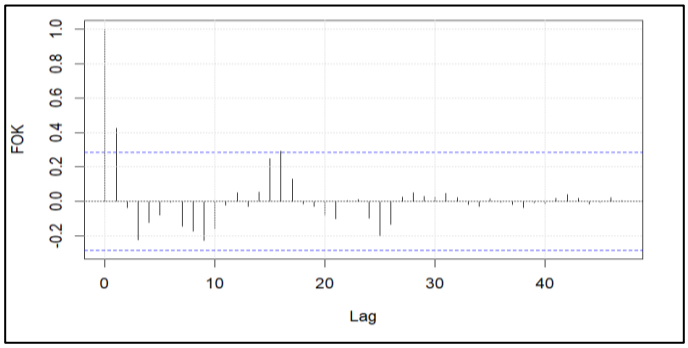


Figure 4. ACF Plot of the Data after Differencing

As shown in Figure 4, after applying the Box-Cox transformation and first-order differencing, the ACF pattern exhibited a cut-off at lag 1, indicating that the data had become stationary in mean. The results of the Augmented Dickey-Fuller (ADF) test at a 5% significance level produced a p-value of 0.01, which was less than 0.05. Therefore, it can be concluded that the data had achieved stationarity in mean.

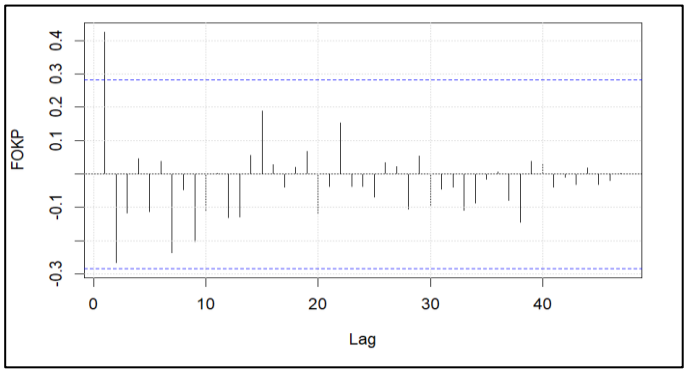


Figure 5. PACF Plot of the Data after Differencing

As shown in Figure 4, the ACF values exhibited a cut-off after lag 1. Furthermore, Figure 5 shows that the PACF values also exhibited a cut-off after lag 1. Based on these findings, three tentative ARIMA models were identified, as presented below.

ARIMA (0,1,1)

$$Z_t^* = \frac{(1-\theta_1 B)}{(1-B)^d} a_t = Z_{t-1}^* - \theta_1 a_{t-1} + a_t \tag{8}$$

ARIMA (1,1,0)

$$Z_t^* = \frac{1}{(1-\phi_1 B)(1-B)} a_t = (1+\phi_1) Z_{t-1}^* - \phi_1 Z_{t-2}^* + a_t \tag{9}$$

ARIMA (1,1,1)

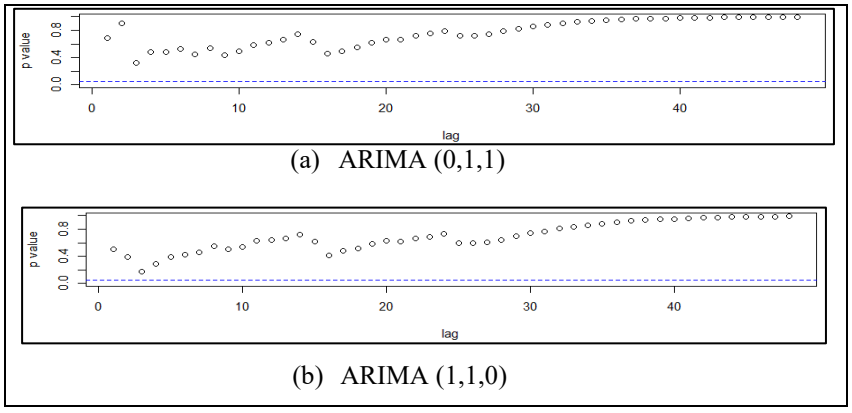
$$Z_t^* = \frac{(1-\theta_1 B)}{(1-\phi_1 B)(1-B)} a_t = (1+\phi_1) Z_{t-1}^* - \phi_1 Z_{t-2}^* - \theta_1 a_{t-1} + a_t \tag{10}$$

The next step was parameter estimation for the candidate ARIMA models, followed by significance testing of each model parameter using the t-test. The estimation and significance testing results are presented in Table 2.

Table 2. Parameter Estimation and Significance Test Results for ARIMA Models

ARIMA	Parameter	Estimate	t_{value}	df	$t_{(0.025;df)}$	*p-value*	Decision
(0,1,1)	θ_1	0.4484	4.3391	48	2.0106	7.329×10^{-5}	Reject H_0
(1,1,0)	ϕ_1	0.4485	3.4759	48	2.0106	0.0011	Reject H_0
(1,1,1)	θ_1	0.2308	1.0229	47	2.0117	0.3116	Fail to Reject H_0
	ϕ_1	0.2998	1.5075			0.1384	Fail to Reject H_0

The parameter significance test results in Table 2 indicate that the ARIMA models with significant parameters were ARIMA(0,1,1) and ARIMA(1,1,0). These two models were subsequently evaluated through diagnostic checking.



(a) ARIMA (0,1,1)

(b) ARIMA (1,1,0)

Figure 6. Residual Plots of the ARIMA Models

Figure 6 shows that the p-values of the Ljung-Box test for the ARIMA(0,1,1) and ARIMA(1,1,0) models were greater than 0.05, with all p-values located above the significance level line. This indicates that the residuals of both models were free from autocorrelation.

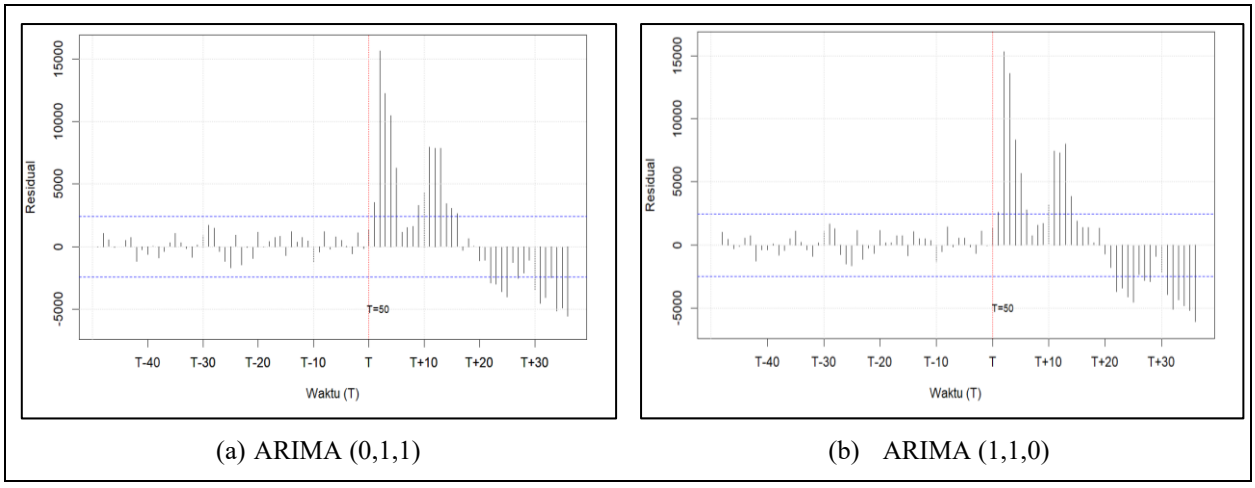
Table 3. Results of the Residual Normality Test

ARIMA	W_{value}	$W_{critical\ value}$	*p-value*	Decision
(0,1,1)	0.9834	0.947	0.7137	Fail to Reject H_0
(1,1,0)	0.9809	0.947	0.6044	Fail to Reject H_0

The residual normality test was conducted using the Shapiro-Wilk test. The results presented in Table 3 indicate that the residuals of both models followed a normal distribution.

4.4. Intervention ARIMA Modeling Using the Step Function

The next stage involved constructing the intervention model based on the ARIMA models that satisfied the diagnostic tests by first identifying the appropriate intervention orders. The identification process was carried out by examining the residual patterns of the Indonesian nickel HMA data for the period from February 2022 to February 2025. Therefore, forecasts for the next 37 periods were generated using both ARIMA models to obtain the residual values. The resulting residuals were then visualized in Figure 7 and used as the basis for determining the intervention orders in the intervention modeling process..



(a) ARIMA (0,1,1) (b) ARIMA (1,1,0)

Figure 7. Residual Plots of the ARIMA Models

Based on Figures 7(a) and 7(b), at the intervention point (T = 50, February 2022) the residual values were still within the significance limits. The residuals began to exceed the significance limits at T+1 (T = 51), indicating a one-period delay and resulting in a delay order of $b = 1$. The increasing residual pattern from T to $T + 2$ followed by a decline indicates an order of $s = 2$, while the absence of any specific pattern thereafter led to the selection of $r = 0$. In addition, several residuals remained outside the significance limits after the intervention period, indicating that the impact of the Russia-Ukraine conflict on Indonesian nickel HMA was long-term in nature. Therefore, this study employed the step function because it is more appropriate for representing persistent intervention effects than the pulse function, which is intended to capture temporary impacts.

After obtaining the intervention ARIMA(0,1,1) and intervention ARIMA(1,1,0) models, the next step was parameter estimation and significance testing for the intervention model parameters.

Tabel 4. Parameter Estimation and Significance Test Results for the Intervention ARIMA Models

Model	Parameter	Estimate	t_{value}	$t_{(0.025;df)}$	*p-value*	Decision
intervensi ARIMA (0,1,1)	θ_1	−0.42169	−4.08	1.9893	<0.0001	Reject H_0
	ω_0	6.280.2	1.77	1.9893	0.0767	Fail to Reject H_0
	ω_1	−34.828.4	−9.12	1.9893	<0.0001	Reject H_0
	ω_2	43.067.5	12.04	1.9893	<0.0001	Reject H_0
intervensi ARIMA (1,1,0)	ϕ_1	0.47291	4.77	1.9893	<0.0001	Reject H_0
	ω_0	7.355.3	2.15	1.9893	0.0318	Reject H_0
	ω_1	−34.933.1	-9.22	1.9893	<0.0001	Reject H_0
	ω_2	44.380.2	12.80	1.9893	<0.0001	Reject H_0

Based on Table 4, the intervention ARIMA(0,1,1) model contained one parameter with a p-value greater than 0.05, indicating that the parameter was not statistically significant and, therefore, the model was not suitable for forecasting purposes. In contrast, all parameters in the intervention ARIMA(1,1,0) model were statistically significant. Consequently, diagnostic checking was performed on this model.

Residual independence was evaluated using the p-value plot of the Ljung–Box test, as presented in Figure 7.

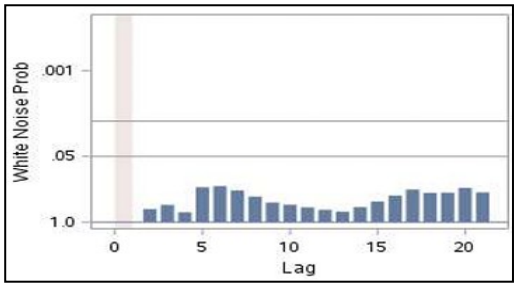


Figure 8. p-value Plot of the Ljung-Box Test

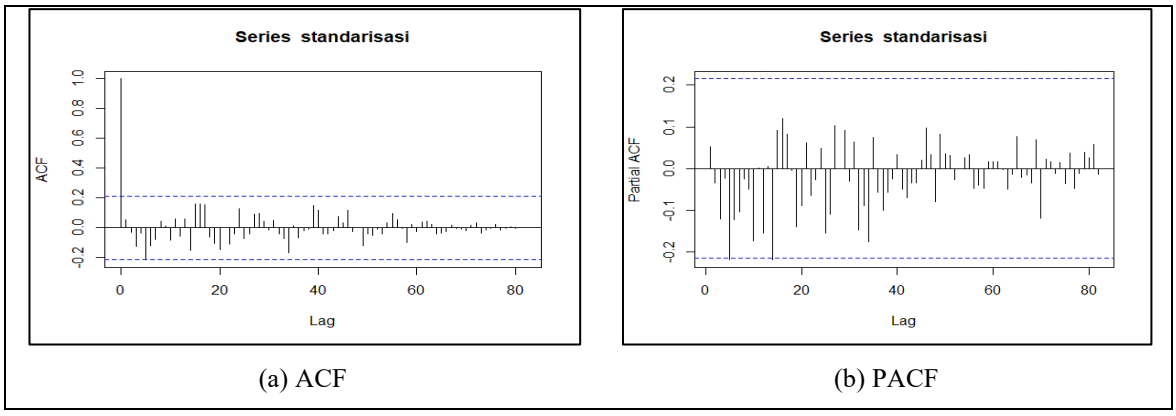
In Figure 8, the bars represent the p-values of the Ljung–Box test. The intervention ARIMA(1,1,0) model with the step function produced p-values ranging from 0.05 to 1.00, indicating that all p-values were greater than 0.05. Therefore, it can be concluded that the residuals of the model were free from autocorrelation. Furthermore, residual normality was assessed using the Shapiro-Wilk test, which yielded a p-value of 0.2767, greater than 0.05, indicating that the residuals followed a normal distribution.

The intervention ARIMA(1,1,0) model satisfied both the parameter significance test and the diagnostic tests, indicating that the model was suitable for prediction and forecasting purposes. The RMSE and MAPE calculations showed that the intervention ARIMA(1,1,0) model with the step function produced an RMSE value of 1,103.3123 and a MAPE value of 4.9295%, indicating a high level of forecasting accuracy since the MAPE value was below 10%. Therefore, this model can be used to forecast Indonesian nickel HMA for the next 12 months, from March 2025 to February 2026.

4.5. Hybrid Intervensi-NN

The implementation of the hybrid Intervention–NN model began with the determination of input variables, which consisted of the residuals obtained from the intervention ARIMA(1,1,0) model with a step function. These residuals were first standardized to match the activation function used in this study, namely the bipolar sigmoid function. Data

standardization was performed using the min-max method with minimum and maximum values of -0.9 and 0.9, respectively. After standardizing the residuals of the intervention model, the next step involved determining the input variables based on the ACF and PACF plots of the residuals from the intervention ARIMA(1,1,0) model.

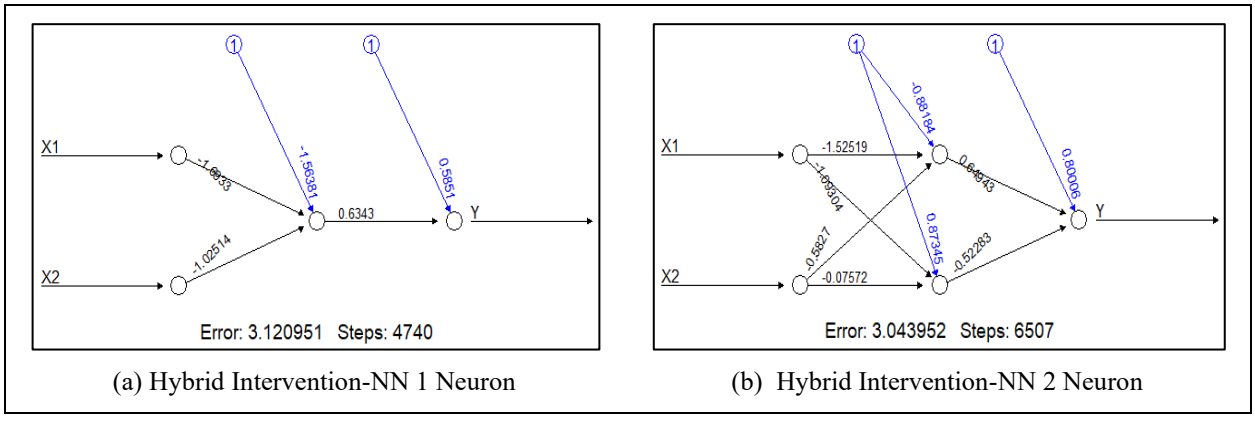


(a) ACF (b) PACF

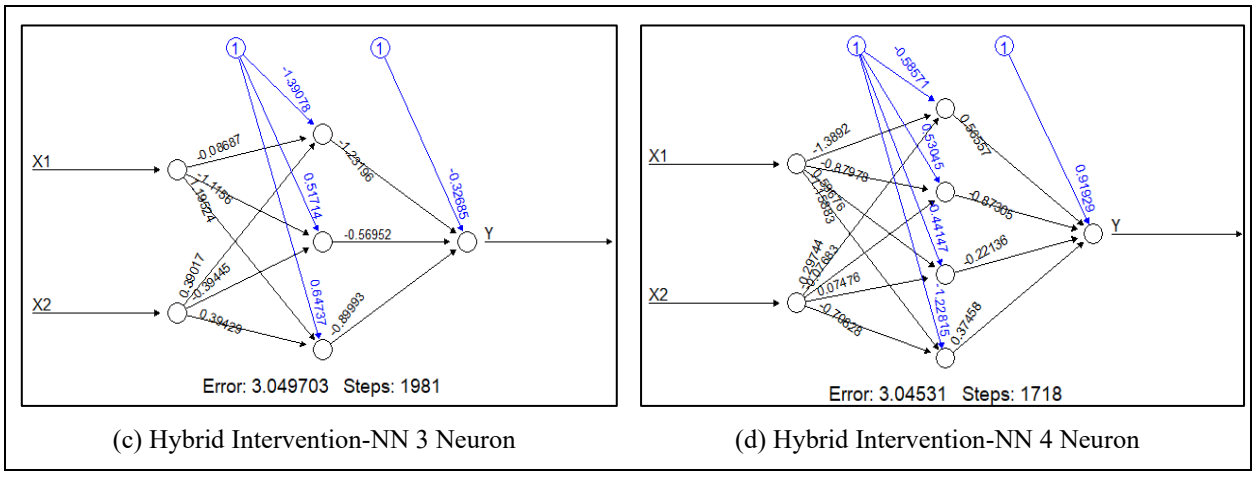
Figure 9. ACF and PACF Plots of the Residuals from the Intervention ARIMA(1,1,0) Model

Based on Figure 9(a), none of the ACF values of the intervention model residuals exceeded the significance limits. Meanwhile, Figure 9(b) shows that the PACF values at lags 5 and 14 exceeded the significance limits, indicating that both lags were significant. Therefore, the input variables used in the Neural Network model were a_{t-5}^{*} as x_1 and a_{t-14}^{*} as x_2. However, since the residuals of the intervention model started at $t = 4$, the corresponding significant lags became lag 8 and lag 17. The output variable used in this study was the standardized residual of the intervention model, denoted by Y_t. The input and output data began at t = 18 k because the highest significant PACF lag was lag 17.

After data standardization and input variable selection, backpropagation training was performed using a Feedforward Neural Network architecture with 1, 2, 3, and 4 hidden neurons and a learning rate of 0.005. The bipolar sigmoid activation function was applied in the input and hidden layers, while a linear activation function was used in the output layer. The training process was terminated when the target error reached 0.01 or when the maximum number of 7,000 iterations was achieved. The following network architectures with 1, 2, 3, and 4 hidden neurons were constructed based on the residuals of the intervention ARIMA(1,1,0) model.



(a) Hybrid Intervention-NN 1 Neuron (b) Hybrid Intervention-NN 2 Neuron



(c) Hybrid Intervention-NN 3 Neuron (d) Hybrid Intervention-NN 4 Neuron

Figure 10. Feedforward Neural Network Architectures Trained Using the Backpropagation Algorithm

After the Neural Network training process using the backpropagation method was completed, the next step was to perform destandardization on the predicted residual values. This process aimed to transform the predicted values obtained during training back to the original data scale prior to standardization. After completing all stages of the Neural Network modeling process, the hybrid Intervention–NN models were constructed using the following equations.

Hybrid intervention ARIMA(1,1,0) step function-NN with 1 neuron

$$\hat{H}_t^* = 1.4729Z_{t-1}^* - 0.4729Z_{t-2}^* + 7{,}355.3S_{t-1}^{(50)} + 24{,}119.4786S_{t-2}^{(50)} - 92{,}354.8416)S_{t-3}^{(50)} + 6{,}872.9404S_{t-4}^{(50)} - 20{,}987.966S_{t-5}^{(50)} + e_t + \hat{N}_{1,t} \quad (7)$$

Hybrid intervention ARIMA(1,1,0) step function-NN with 2 neurons

$$\hat{H}_t^* = 1.4729Z_{t-1}^* - 0.4729Z_{t-2}^* + 7{,}355.3S_{t-1}^{(50)} + 24{,}119.4786S_{t-2}^{(50)} - 92{,}354.8416)S_{t-3}^{(50)} + 6{,}872.9404S_{t-4}^{(50)} - 20{,}987.966S_{t-5}^{(50)} + e_t + \hat{N}_{2,t} \quad (8)$$

Hybrid intervention ARIMA(1,1,0) step function-NN with 3 neurons

$$\hat{H}_t^* = 1.4729Z_{t-1}^* - 0.4729Z_{t-2}^* + 7{,}355.3S_{t-1}^{(50)} + 24{,}119.4786S_{t-2}^{(50)} - 92{,}354.8416)S_{t-3}^{(50)} + 6{,}872.9404S_{t-4}^{(50)} - 20{,}987.966S_{t-5}^{(50)} + e_t + \hat{N}_{3,t} \quad (9)$$

Hybrid intervention ARIMA(1,1,0) step function-NN with 4 neurons

$$\hat{H}_t^* = 1.4729Z_{t-1}^* - 0.4729Z_{t-2}^* + 7{,}355.3S_{t-1}^{(50)} + 24{,}119.4786S_{t-2}^{(50)} - 92{,}354.8416)S_{t-3}^{(50)} + 6{,}872.9404S_{t-4}^{(50)} - 20{,}987.966S_{t-5}^{(50)} + e_t + \hat{N}_{4,t} \quad (10)$$

The best hybrid Intervention-NN model was selected based on the RMSE and MAPE values. The forecasting accuracy results for the models with 1, 2, 3, and 4 hidden neurons are presented as follows.

Table 5. Comparison of RMSE and MAPE Values between the Models

Model	RMSE	MAPE
Intervention ARIMA(1,1,0) Step Function	1,103.3123	4.9295%
Hybrid intervention ARIMA(1,1,0) step function-NN with 1 neuron	1,087.8830	4.8215%
Hybrid intervention ARIMA(1,1,0) step function-NN with 2 neurons	1,074.3652	4.7735%
Hybrid intervention ARIMA(1,1,0) step function-NN with 3 neurons	1,075.3762	4.7995%
Hybrid intervention ARIMA(1,1,0) step function-NN with 4 neurons	1,074.6121	4.7768%

Based on Table 5, the RMSE and MAPE values of the intervention and hybrid Intervention-NN models were relatively similar, and all models were classified as highly accurate forecasting models since their MAPE values were below 10%. However, the model with the smallest forecasting error was the hybrid intervention ARIMA(1,1,0) step function-NN model with 2 neurons. Therefore, this model was selected for forecasting Indonesian nickel HMA. Furthermore, the hybrid modeling approach was shown to reduce forecasting errors compared with the single intervention model.

4.6. Forecasting Using the Best Hybrid Intervention–NN Model

In this study, Indonesian nickel HMA was forecasted for the next 12 periods, namely from March 2025 to February 2026, corresponding to $t = 87,88,\ldots,98$. The forecasting results for Indonesian nickel HMA are presented in Table 6.

Table 6. Forecasting Results of the Hybrid Intervention ARIMA(1,1,0) Step Function-NN with 2 Neurons

t	Forecast ($\hat{H}_t$)	t	Forecast ($\hat{H}_t$)
87	14,439.6179	93	10,278.4574
88	13,955.4475	94	9,580.9106
89	13,024.1912	95	9,227.0705
90	12,653.1577	96	8,087.3859
91	12,182.8656	97	7,491.9820
92	11,125.8377	98	6,793.3724

Based on the forecasting results presented in Table 6, a plot can be constructed to illustrate the comparison between the actual data, fitted values, and forecasts of Indonesian nickel HMA generated by the hybrid intervention ARIMA(1,1,0) step function-NN model with 2 hidden neurons, as shown in Figure 11.

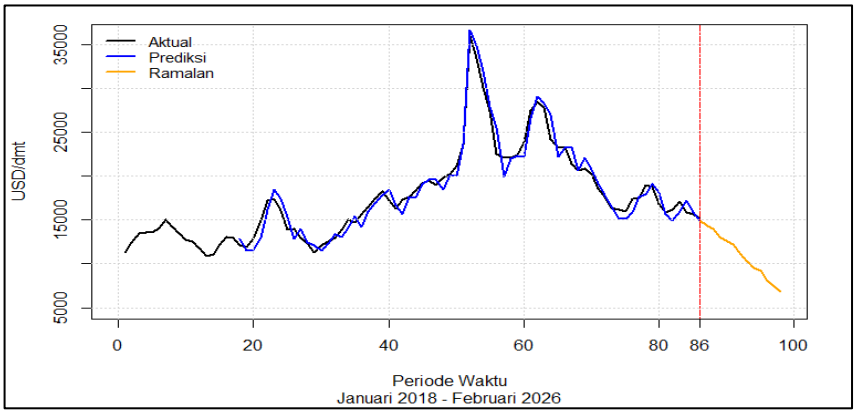


Figure 11. Comparison of Actual Data and Forecasted Values Using the Best Hybrid Intervention ARIMA(1,1,0) Step Function–NN Model

Based on Figure 11, the predicted values closely followed the pattern of the actual data, indicating that the hybrid intervention ARIMA(1,1,0) step function–NN model with 2 hidden neurons had good predictive performance. This finding is further supported by the MAPE value of 4.7735%, which indicates that the model achieved a very high level of forecasting accuracy. Furthermore, the forecasting results suggest a downward trend in Indonesian nickel HMA during the period from March 2025 to February 2026.

5. Conclusion

The results of this study indicate that the most suitable model for forecasting Indonesian nickel HMA for the period January 2018 to February 2025 was the hybrid intervention ARIMA(1,1,0) step function model combined with a Neural Network with 2 hidden neurons. This model produced the smallest forecasting error among all alternative models, with an RMSE value of 1,074.3652 and a MAPE value of 4.7735%, placing it in the highly accurate category. These findings

demonstrate that combining linear approaches (intervention ARIMA) and nonlinear approaches (Neural Network) can improve the forecasting accuracy of time series data affected by external events. The forecasting results indicate that Indonesian nickel HMA is expected to experience a declining trend during the period from March 2025 to February 2026.

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