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Time Series Analysis in Forecasting Nickel Prices Using the ARIMA and Double Exponential Smoothing Methods

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ABSTRACT

Nickel is one of the strategic commodities that plays an important role in global industries, particularly as the primary raw material in the production of stainless steel and electric vehicle batteries. The increasing demand for nickel, driven by technological advancements and the need for more environmentally friendly energy sources, causes nickel prices to fluctuate, making it necessary to employ methods capable of forecasting future price movements. This study aims to forecast nickel prices using the Autoregressive Integrated Moving Average (ARIMA) method and the Double Exponential Smoothing method, as well as to compare the performance of both methods. The data used in this research consist of secondary daily nickel price data with 62 observation periods. The research stages include data preprocessing, stationarity testing, modeling, and model evaluation using Mean Squared Error (MSE) and Root Mean Squared Error (RMSE). The results show that the best ARIMA model is ARIMA(2,1,1), which produces an MSE of 0.2797 and an RMSE of 0.5288. Meanwhile, the Double Exponential Smoothing method results in an MSE of 0.1299 and an RMSE of 0.3604. Based on these evaluation results, the Double Exponential Smoothing method demonstrates better performance than ARIMA in forecasting nickel prices in this study. This method is able to produce more accurate and stable predictions that follow the trend patterns of the data. Therefore, the Double Exponential Smoothing method is recommended as a more optimal approach for nickel price forecasting.

INTRODUCTION

Nickel is one of the mined commodities that plays an important role in various industrial sectors, particularly as the primary raw material in the production of stainless steel and components of electric vehicle batteries (R.M., 2024). Along with the rapid development of technology and the increasing need for more efficient and environmentally friendly energy sources (Mufida et al., 2024), the demand for nickel in the global market continues to increase. This is driven using nickel-based materials in electric vehicle batteries, which are capable of storing energy in large capacities, thereby supporting greater energy efficiency while helping to reduce air pollution compared to the use of conventional fuels. In addition, nickel has become a strategic commodity with high economic value in the international market. Indonesia is known as one of the largest nickel-producing countries in the world, contributing approximately 27% to the global nickel supply (Harahap & Novitasari, 2022). This condition makes the development of the nickel industry have a significant impact on both the national economy and the dynamics of the global commodity market. The international nickel price tends to fluctuate over time, one of the factors being the high demand from various industrial sectors (Carista et al., 2025a).

To obtain information regarding nickel price movements, historical nickel price data from previous periods can be utilized. The collection of nickel price data over time forms a time series that can be used to forecast future nickel prices. Time series forecasting methods are employed to identify the characteristics of the data as well as the information contained within it, thereby enabling the generation of more accurate predictions (PENGGUNAAN METODE ARIMA DALAM MERAMAL PERGERAKAN INFLASI, n.d.). Several methods commonly used in time series forecasting include the Autoregressive Integrated Moving Average (ARIMA) and Double Exponential Smoothing, both of which are known for their ability to model the characteristics of time series data. Previous studies have shown that the ARIMA, SVR, and hybrid ARIMA–SVR methods can be applied to predict nickel prices, with results indicating that the SVR method provides the best performance based on MAPE, RMSE, and MAE values, producing the lowest MAPE of 0.2532% (Carista et al., 2025b). Another study compared the ARIMA and SARIMA methods in predicting traffic load data, and the results showed that the ARIMA model performed better based on the MAE, MAPE, and RMSE metrics (Peychinov et al., 2025). The Double Exponential Smoothing method showed good performance with a MAPE value of 0.76% in forecasting the Consumer Price Index (CPI) in Yogyakarta City, indicating that the method is accurate and suitable for use in forecasting (Asmaradana et al., 2023). Forecasting the value of consumer goods imports using the Double Moving Average (DMA) and Double Exponential Smoothing (DES) methods shows that the DES method provides the best performance based on the lowest MSE and MAPE values (Darina et al., 2024).

The ARIMA method is widely used due to its ability to model stationary data (Melina et al., 2024) and to identify linear patterns in historical data (Gempati et al., 2025). In addition, the Double Exponential Smoothing method is also widely used in time series forecasting because it can accommodate both trend and level components in the data (Ewaldo et al., 2025). Previous studies have shown that both methods have good accuracy in predicting time series data, depending on the characteristics of the data used. However, differences in data characteristics and the observation period of nickel prices necessitate further analysis to determine the most appropriate forecasting method. Therefore, this study aims to predict nickel prices using the ARIMA and Double Exponential Smoothing methods and to compare the performance of both methods in generating accurate predictions based on RMSE and MSE values. The findings of this study are expected to provide insights into future nickel price movements and serve as a consideration for decision-making by industry stakeholders, investors, and policymakers.

METHODS

This study employs a quantitative approach using time series methods to forecast nickel prices. The methods used in this research are the ARIMA and Double Exponential Smoothing (DES). These two methods were selected because they are capable of modeling time series data with a relatively limited number of observations and can capture trend patterns within the data.

Data

The data used in this study consist of secondary data in the form of daily nickel prices obtained from the Katadata website(Agus Dwi Darmawan, 2026). The dataset consists of daily nickel price values sourced from Westmetal and measured in United States dollars (USD). The observation period covers three months, from December 10, 2025 to March 10, 2026. For the purposes of model estimation and validation, the dataset is divided into training and testing sets. The training set, comprising 80% of the data, is used to estimate the parameters of the ARIMA and Double Exponential Smoothing (DES) models, while the remaining 20% is used for model testing and performance evaluation.

Stationarity

Stationarity is one of the fundamental assumptions in time series modeling using the ARIMA method. A time series is considered stationary if it has constant mean, variance, and covariance over time (Sains & Seni Its, 2021). A time series is considered stationary in mean if the data fluctuate around a constant horizontal line over time (Lubis et al., 2021):

$$E(z_t) = E(z_{t+k}) = \mu$$

If the data are non-stationary, a differencing process is applied until stationarity is achieved. The differencing process of order $d$can be expressed as follows:

$$w_t = (1 - B)^d Z_t$$

Power transformation can be applied to stabilize the variance of non-stationary data. The following represents the power transformation:

$$T(Z_t) = \begin{cases} z_t^{\lambda} - 1, & \\ In(Z_t), & \lambda = 0 \end{cases}$$

Autocorrelation analysis

The next step in the analysis is to construct the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots, which play a crucial role in identifying the optimal order of the Autoregressive (AR) and Moving Average (MA) components in the model (Nahuway et al., 2025). The ACF plot is used to determine the order of the Moving Average (MA) model and to assess whether the data are stationary. A slowly decaying ACF pattern indicates that the data are non-stationary, whereas a pattern that rapidly approaches zero suggests that the data are stationary. Meanwhile, the Partial Autocorrelation Function (PACF) measures the direct correlation between the current observation and a specific lag by removing the influence of intermediate lags. The PACF serves as the primary tool for determining the order of the non-seasonal autoregressive component (p) as well as the seasonal autoregressive component (P) (Shumway, 2017)

ARIMA Modelling

The ARIMA architecture mathematically maps the future value of a variable as a linear combination of its own past values (AR terms), past forecast errors (MA terms), and the differencing required to achieve stationarity (Yuliawanti et al., 2021). This model is expressed in the form ARIMA(p, d, q), where p denotes the autoregressive order, d represents the degree of differencing, and q refers to the moving average order (Melina et al., 2024). The ARIMA model is defined as follows (Jayanti et al., 2025)

$$\phi_p(B)(1-B)dX_t = \theta_q(B)e_t$$

Description :

ϕ_p : Autoregressive parameter of order

X_t : Observed data at time

d : Number of differencing operations applied

θ_q : Moving average parameter of order

e_t : Residual error term

Akaike Information Criterion

The Akaike Information Criterion (AIC) is employed as a model selection criterion to identify the best-fitting model. AIC evaluates the trade-off between model goodness-of-fit and model complexity, thereby preventing overfitting. A model with a lower AIC value is preferred, as it indicates a better balance between accuracy and parsimony. In this study, several candidate ARIMA models are compared based on their AIC values to determine the most optimal model. The AIC formula is given as follows (Abror Gustiansyah et al., 2023) :

$$AIC = In\left(\frac{\sum_{t=1}^{n} e_t^2}{T}\right) + \frac{2p}{T}$$

Where $\sum_{t=1}^{n} e_t^2$ represents the sum of squared residuals, p denotes the number of parameters in the model, and denotes the number of observations.

Double Exponential Smoothing Modelling

The Double Exponential Smoothing method is used to capture trend patterns in time series data (Pirmanto, 2024). This method is an extension of the Single Exponential Smoothing approach by incorporating a trend component. The Double Exponential Smoothing model uses two main parameters: the level smoothing parameter (α) and the trend smoothing parameter (β) (Asmaradana et al., 2023). Parameter estimation is performed automatically by the system to obtain the best model based on the training data. The resulting model is then used to generate forecasts for the testing period. The formulas used in the Double Exponential Smoothing method can be defined according to the following equations (Habsari et al., 2020):

Single Exponential Smoothing Value :

$$S'_t = \alpha X_t + (1 - \alpha) S'_{t-1}$$

Double Exponential Smoothing Value :

$$S''_t = \alpha S'_t + (1 - \alpha) S''_{t-1}$$

Level Component (Constant) :

$$\alpha_t = S'_t + (S'_t - S''_t) = 2S'_t - S''_t$$

Trend Component :

$$b_t = \frac{\alpha}{1 - \alpha}(S'_t - S''_t)$$

Forecasting Value :

$$F_{t+m} = \alpha_t + b_t m$$

Description :

S'_t : Single Exponential Smoothing value at time
α : Exponential smoothing parameter ($0 < \alpha < 1$)
X_t : Actual data at time
S'_{t-1} : Single Exponential Smoothing value at time period $t - 1$
S''_t : Double Exponential Smoothing value at time period t
S''_{t-1} : Double Exponential Smoothing value at time period $t - 1$
α_t : The constant value at time period t
b_t : Trend component at time period t
m : Number of periods ahead to be forecast
F_{t+m} : Forecast value for m periods ahead

RMSE

Model performance evaluation is carried out by comparing the predicted values with the actual values in the testing dataset. The performance metrics used in this study are the Mean Squared Error (MSE) and the Root Mean Squared Error (RMSE). RMSE is the square root of MSE and has the same unit as the original data, making it easier to interpret. The formula for the Root Mean Squared Error (RMSE) is shown in equation (Shakeel et al., 2025) :

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

MSE

MSE measures the average squared difference between the actual values and the predicted values. The formula for Mean Squared Error (MSE) is given in equation (Nuha, 2024)

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

RESULT AND DISCUSSIONS

Descriptive Analysis

Based on the nickel price graph from December 2025 to March 2026, the price movement exhibits a fluctuating pattern with an upward trend in the early period, where prices increase from approximately 14.3–15 to a peak of around 18–19 by the end of January 2026. This increase indicates a strong positive trend before experiencing a sharp decline in early

February to the range of 16.8–17.5, suggesting a market correction following the upward phase. Subsequently, from mid-February to March 2026, prices tend to move relatively stable within the range of 17–18 with lower fluctuations compared to the previous period, reflecting a more balanced market condition. Overall, this pattern demonstrates phases of growth, peak, decline, and stabilization, indicating relatively high volatility, particularly in the mid-observation period. For further analysis, the data will be modeled using Autoregressive Integrated Moving Average (ARIMA) and Double Exponential Smoothing (DES) methods, with a data split of 80% for training and 20% for testing to evaluate the forecasting performance of the models.

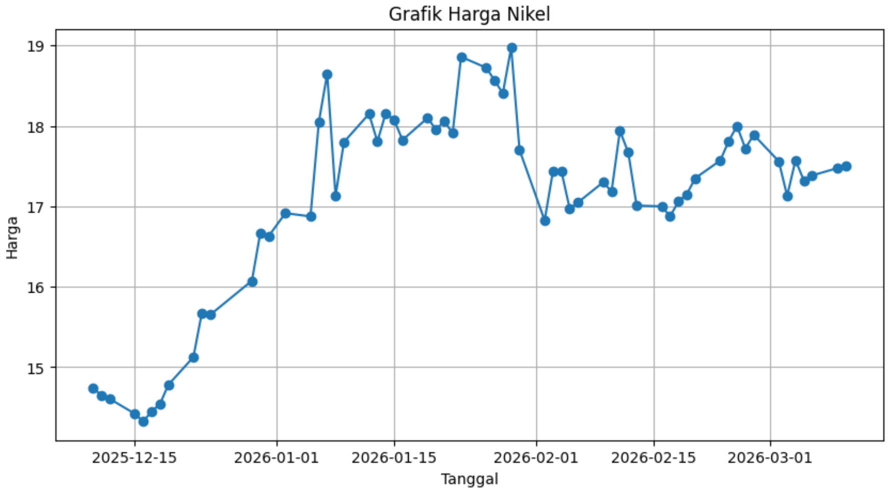

Figure 1. Graph of Nickel Price Data from the Dataset

ARIMA Model

At this stage, the ARIMA method is used to model and forecast nickel prices. Before conducting the modeling process, several preliminary steps were performed to ensure that the data met the assumptions required in time series analysis. The first step was testing the stationarity of variance using the Box–Cox transformation. The test result showed a lambda value of 5.589, indicating that the data did not have stable variance. Therefore, a Box–Cox transformation was applied to stabilize the variance. After transformation, a lambda value of 1.000000014 was obtained, indicating that the data satisfied the assumption of variance stationarity.

Next, stationarity in the mean was examined using the Augmented Dickey-Fuller (ADF) test. The initial test produced a p-value of 0.252, meaning that the data were not stationary. To address this, differencing was applied to the data. After differencing, the ADF test was performed again, yielding an ADF statistic of −7.233 with a p-value of 1.97×10^{-10}. These results indicate that the data had become stationary and were ready for modeling. The next stage was model identification by examining the autocorrelation and partial autocorrelation patterns through the ACF plot shown in Figure 2 and the PACF plot shown in Figure 3.

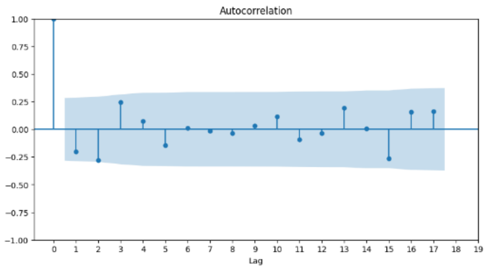

Figure 2. ACF Plot

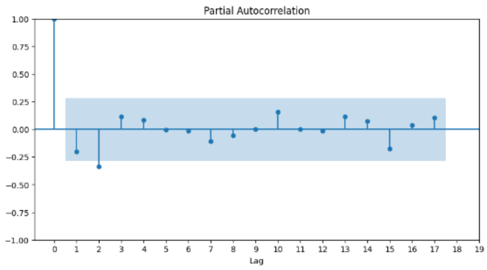

Figure 3. PACF Plot

Based on the ACF plot, it can be observed that there is no clear cut-off pattern at any specific lag; instead, the autocorrelation values gradually decrease (tailing off). This indicates that the Moving Average (MA) component is likely to have an order greater than zero, although it is not dominant at any particular lag.

Meanwhile, the PACF plot shows significant spikes at the initial lags, particularly at lag 1 and lag 2, after which the partial autocorrelation values tend to fall within the confidence interval. This pattern indicates the possible presence of a low-order Autoregressive (AR) component, such as AR(1) or AR(2). Overall, the combination of a gradually declining ACF pattern and a PACF pattern with an early cut-off suggests that the data can be modeled using a combination of AR and MA components, making the Autoregressive Integrated Moving Average (ARIMA) approach appropriate for use.

Based on the interpretation of the ACF and PACF plots, several candidate models were identified, namely ARIMA(1,1,1), ARIMA(2,1,1), ARIMA(1,1,2), ARIMA(2,1,2), ARIMA(2,1,0), and ARIMA(0,1,2). The best model was selected using the Akaike Information Criterion (AIC). The AIC value is used to assess model quality by balancing goodness of fit and model complexity, where the model with the smallest AIC value is chosen as the best model. The AIC values for each model are presented in the following Table 1.

Table 1. The AIC values for each ARIMA model

Model ARIMA	AIC
ARIMA (1,1,1)	1319,191192
ARIMA (2,1,1)	1314,279631
ARIMA (1,1,2)	1322,930765
ARIMA (2,1,2)	1316,238182
ARIMA (2,1,0)	1324,174269
ARIMA (0,1,2)	1318,805636

Based on the AIC comparison chart, it can be seen that the ARIMA(2,1,1) model has the lowest AIC value among all candidate models, approximately 1314. This indicates that the ARIMA(2,1,1) model is the most optimal in representing the data compared to other candidate models such as ARIMA(1,1,1), ARIMA(1,1,2), ARIMA(2,1,2), ARIMA(2,1,0), and ARIMA(0,1,2). Meanwhile, the ARIMA(2,1,0) model has the highest AIC value, suggesting that it is less capable of capturing the data patterns effectively. The differences in AIC values across the models indicate that the choice of AR and MA parameter orders significantly influences the model's performance in modeling time series data.

Thus, based on the AIC criterion, the Autoregressive Integrated Moving Average model ARIMA(2,1,1) is selected as the best model and is subsequently used for forecasting nickel prices. The performance evaluation of the selected model was conducted using the Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) metrics to measure the prediction errors relative to the actual values. The results show an MSE value of 0.2797 and an RMSE value of 0.5288. These values indicate that the model exhibits a relatively low error rate, suggesting that it is capable of producing fairly accurate predictions of nickel price movements. The relatively small RMSE value implies that the difference between the predicted and actual values tends to be low. This demonstrates that the ARIMA(2,1,1) model is effective in capturing historical data patterns and can be considered a reliable model for forecasting nickel prices.

Double Exponential Smoothing Model

The modeling process for this method requires determining the smoothing parameters, namely the level parameter (α) and the trend parameter (β). The parameter values were determined through several trials to obtain the combination that produces the smallest forecasting error. Subsequently, the Double Exponential Smoothing model was evaluated to assess its accuracy in predicting nickel prices. The evaluation was conducted using the Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) metrics.

Based on the calculation results, the model produced an MSE value of 0.1299 and an RMSE value of 0.3604. These values indicate that the error generated by the model is relatively small, demonstrating that the model is capable of providing sufficiently accurate predictions compared to the actual data.

Model Selection

Based on the forecasting results obtained, there is a noticeable difference in performance between the Autoregressive Integrated Moving Average (ARIMA) method and the Double Exponential Smoothing method. The ARIMA(2,1,1) model produced an MSE value of 0.2797 and an RMSE value of 0.5288, whereas the Double Exponential Smoothing method yielded an MSE value of 0.1299 and an RMSE value of 0.3604. These results indicate that the Double Exponential Smoothing method provides more accurate predictions than the ARIMA model. The forecasting results for nickel prices using the ARIMA and Double Exponential Smoothing methods are presented in Table 2, based on the observation period from February 20, 2026, to March 10, 2026.

Table 2. The forecasting results for nickel prices using the ARIMA and Double Exponential Smoothing methods

Date	Price	
	ARIMA	Doubel Exponential Smoothing
2026-02-20	17.350	17.187659
2026-02-23	17.570	17.238423
2026-02-24	17.810	17.289187
2026-02-25	18.000	17.339952
2026-02-26	17.720	17.390716
2026-02-27	17.890	17.441480
2026-03-02	17.560	17.492244
2026-03-03	17.130	17.543008

2026-03-04	17.575	17.593772
2026-03-05	17.320	17.644536
2026-03-06	17.385	17.695301
2026-03-09	17.475	17.746065
2026-03-10	17.505	17.796829

Based on the forecasting results, it can be observed that the ARIMA method produces prediction values that tend to follow the fluctuations of the actual data, with values rising and falling in accordance with historical nickel price patterns. For example, on February 25, 2026, the predicted price was 18,000, which then decreased to 17,720 on February 26, 2026, demonstrating the model's ability to capture dynamic changes in the data. Meanwhile, the Double Exponential Smoothing method shows a smoother prediction pattern that gradually increases over time. The predicted values start at 17,187659 on February 20, 2026, and continue to rise until reaching 17,796829 on March 10, 2026. This pattern reflects the characteristic of the method, which places greater emphasis on the trend component rather than short-term fluctuations.

When compared, the ARIMA forecasting results are more responsive to short-term price changes, whereas Double Exponential Smoothing provides more stable and consistent trend-following predictions. However, based on the previously obtained error evaluation metrics, the Double Exponential Smoothing method demonstrates better accuracy than ARIMA.
Thus, although both methods are capable of forecasting nickel prices, Double Exponential Smoothing outperforms ARIMA in generating stable and accurate predictions, while ARIMA is more effective in capturing short-term fluctuations in the data.

CONCLUSIONS AND SUGGESTIONS

Based on the results of the study, it can be concluded that the Autoregressive Integrated Moving Average (ARIMA) and Double Exponential Smoothing methods can be used to forecast nickel prices based on historical data. The modeling results show that the best ARIMA model obtained is ARIMA(2,1,1), which produces an MSE value of 0.2797 and an RMSE value of 0.5288. Meanwhile, the Double Exponential Smoothing method yields an MSE value of 0.1299 and an RMSE value of 0.3604, indicating a lower error rate compared to the ARIMA model. Based on these findings, the Double Exponential Smoothing method demonstrates better performance in predicting nickel prices in this study. This method is able to generate more stable predictions that closely match the actual values, particularly in capturing the trend component of the data. On the other hand, the ARIMA method is more effective in representing short-term fluctuations but results in higher prediction errors.

Therefore, the selection of an appropriate forecasting method should be aligned with the characteristics of the data used. In this study, the Double Exponential Smoothing method is recommended as the more optimal model for forecasting nickel prices. The results of this research are expected to serve as a reference for industry practitioners, investors, and policymakers in making decisions related to future nickel price movements.

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