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APPLICATION OF THE ARIMA MODEL FOR STOCK PRICE PREDICTION OF PT ADARO ENERGY TBK: A TIME SERIES ANALYSIS DURING THE ENERGY TRANSITION PERIOD

Faiz Zamzami[1]

Azzahra Ramadhani[2]

Azizah Nurul Putri[3]

Wahyuni Windasari[4*]

[1,2,3,4]*Universitas Putra Bangsa Kebumen, Indonesia*

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wahyuwindasari@gmail.com

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Abstract || This study examines the stock price movements of PT Adaro Energy Tbk (ADRO) using the Autoregressive Integrated Moving Average (ARIMA) model, with a particular focus on the energy transition period. Employing daily closing price data from December 27, 2023, to December 24, 2024, this research utilizes a quantitative time series approach to develop a robust predictive model. The analysis results indicate that the ARIMA (2,1,0) model demonstrates the best performance based on the Sum of Squared Errors (SSE), Akaike Information Criterion (AIC), and Schwarz Information Criterion (SIC). This model effectively captures stock price movement patterns, including significant volatility observed during the business unit spin-off period. The forecast for the next 20 periods suggests a stable trend with a satisfactory level of accuracy. These findings offer valuable insights for investors and analysts in understanding the stock price dynamics of energy companies undergoing business transformations.

Keywords || Arima; Stock Prediction; Time Series; Energy Transition

Abstrak || Penelitian ini menganalisis pergerakan harga saham PT Adaro Energy Tbk (ADRO) menggunakan model ARIMA (Autoregressive Integrated Moving Average) dengan fokus pada periode transisi energi. Menggunakan data harian harga penutupan saham dari 27 Desember 2023 hingga 24 Desember 2024, studi ini menerapkan pendekatan kuantitatif time series untuk mengembangkan model prediksi yang akurat. Hasil analisis menunjukkan bahwa model ARIMA (2,1,0) memberikan performa terbaik berdasarkan kriteria SSE, AIC, dan SIC. Model ini berhasil menangkap pola pergerakan harga saham, termasuk volatilitas signifikan yang terjadi selama periode spin-off unit usaha. Peramalan 20 periode ke depan menunjukkan tren yang stabil dengan tingkat akurasi yang memadai. Temuan ini memberikan kontribusi penting bagi investor dan analis dalam memahami dinamika harga saham perusahaan energi yang sedang menjalani transformasi bisnis.

Katakunci || Arima; Prediksi Saham; Time Series; Transisi Energi

Introduction

Investment refers to the allocation of a certain amount of funds or assets into a company or project with the expectation of generating profits or benefits in the future. This activity can take various forms, such as investments in the real estate sector, bonds, or direct business ventures. When executed with the proper strategy, investment can serve as an effective means of increasing asset value and achieving long-term financial objectives. One appealing form of investment is the stock market, which includes ownership of company shares or other commodities. The stock market presents significant profit potential for investors who possess a strong understanding of market dynamics and are adept at managing risk. Although price fluctuations can present challenges, a well-developed investment strategy can help investors maximize returns while minimizing potential losses (Julian & Pribadi, 2021).

One widely chosen investment type is stock capital investment. Stocks are financial instruments that represent ownership in a company, allowing investors to share in its growth and potentially benefit from dividends and capital appreciation. Shareholders are also entitled to a portion of the company's assets according to their ownership stake. These rights include receiving dividends, attending general shareholder meetings (GSM), and participating in key decision-making processes related to the company. Thus, stock investment not only offers the potential for financial gain but also provides investors with a role in the company's business dynamics (Rizki et al., 2021).

In Indonesia, stocks are an attractive option for investors due to their potential for high returns. The stock market presents significant profit opportunities, particularly for those with a deep understanding of fundamental and technical analysis. With the right approach, investors can capitalize on stock price movements to achieve both short-term and long-term gains. However, stock investments are also associated with high risk, commensurate with the potential returns. Investing in stocks carries substantial risk due to the volatility and stochastic nature of stock prices, which are influenced by various economic, political, and market sentiment factors (Irawan, 2019). Therefore, investors must implement effective risk management strategies to navigate market volatility and minimize potential losses.

Given the unpredictable and volatile nature of stock price movements, it is essential to employ a method that can accurately predict stock values. An effective prediction technique should be capable of identifying historical patterns, accommodating random variables, and providing reliable projections. With more precise predictions, investors can make more informed decisions and mitigate the risks associated with market volatility. One commonly used method for predicting stock prices is the Autoregressive Integrated Moving Average (ARIMA) model. This method is adept at identifying trend patterns in time-series data, providing more accurate forecasts of future stock price movements. By analyzing historical data, ARIMA assists investors in recognizing trends and patterns that inform investment strategies.

The ARIMA model is based on the assumption that observed data follows a predictable pattern that can be analyzed to forecast future values. Using a statistical approach that combines autoregressive (AR), differencing (I), and moving average (MA) components, ARIMA is capable of identifying historical patterns and generating reliable projections (Rusminto et al., 2024). The ARIMA model has been widely employed in various studies to predict financial data, including stock price movements. As noted by Choo et al. (2024), ARIMA demonstrates high accuracy in predicting time-series data with complex seasonal or trend patterns. Its ability to capture data dynamics makes ARIMA a popular tool among analysts and investors for understanding market movements and reducing uncertainty in investment decisions.

For instance, research conducted by Ilu & Prasad (2023); Maulidya et al. (2024) demonstrate that the ARIMA method effectively captures stock price fluctuations in the energy sector. By analyzing historical patterns and accommodating dynamic price changes, ARIMA provides more accurate projections of stock movements in this sector. This evidence underscores the method's efficacy in addressing the market volatility commonly observed in the energy industry. Similarly, a study by Rusminto et al. (2024) applies the ARIMA method to forecast the stock price of GOTO, a prominent company. The findings of their study reveal that the ARIMA model produces predictions that align with the actual movement of GOTO's stock prices, achieving a high degree of accuracy. These results further support the validity of ARIMA as a reliable tool for stock market analysis, aiding investors in making more precise and informed investment decisions.

This study utilizes the closing stock price data of PT Adaro Energy Tbk (ADRO), a leading company in the energy and mining sector, to forecast stock price values. PT Adaro Energy Tbk (ADRO) is a major Indonesian corporation primarily engaged in coal mining, with expanding ventures in renewable energy and logistics services. As one of Indonesia's largest energy companies, ADRO's stock price movements significantly influence the capital market, not only within the energy sector but also in the broader national economy. Furthermore, ADRO's stock price volatility reflects global energy sector dynamics, such as fluctuations in international coal prices, energy policies, and domestic supply and demand factors. Given ADRO's strategic role, analyzing and forecasting its stock price are crucial for assisting investors, analysts, and other stakeholders in making data-driven decisions. This study aims to contribute to understanding the patterns of ADRO's stock price movements and to provide a foundation for developing investment strategies within the energy sector.

The objective of this study is to forecast ADRO's stock prices using the ARIMA model, with a focus on forecasting over multiple future time periods. The study aims to offer additional insights to investors through the application of a meticulously developed ARIMA model. Various diagnostic tests are performed to ensure the model's accuracy and precision, making the stock movement predictions reliable for investment decision-making. Furthermore, this research contributes to enriching the existing literature on the application of ARIMA in stock analysis within the energy sector. As a result, this study holds both academic relevance and practical significance.

Methodology

This study employs a quantitative approach to time series data to analyze stock price movements. The model used is ARIMA (Auto Regressive Integrated Moving Average), which is designed to capture historical patterns and predict future values based on the assumption of data stationarity. The analysis utilizes the closing stock price data of ADRO.JK, obtained from the Yahoo Finance website, covering the period from December 27, 2023, to December 24, 2024.

For data analysis, this study uses EViews statistical software as the primary tool for processing the ADRO.JK stock price data. EViews was selected due to its effectiveness in handling time series data, including the construction, testing, and analysis of ARIMA models. The use of this software facilitates faster, more accurate, and more efficient calculations, thereby ensuring the reliability of the analysis results. The process for determining the ARIMA model involves the following steps:

Collecting Historical ADRO Stock Price Data

The data used consists of secondary data, with a total of 238 daily observations collected from Monday to Friday, excluding holidays. The observation data were sourced from Yahoo (2024).

Table 1. Sample ADRO stock price

Date	Close Price
December 27, 2023	2.590,00
December 28, 2023	2.580,00
December 29, 2023	2.380,00
January2, 2024	2.490,00
January 3, 2024	2.410,00

Data Stationarity Test

A stationarity test is conducted before analyzing time series data. Data is considered stationary if it does not exhibit sharp declines or growth, thus forming a generally horizontal pattern over time (Rahmawati et al., 2021). The stationarity of the data can be tested using the Augmented Dickey-Fuller (ADF) test, where the data is declared stationary if the ADF test probability value is less than 5%, and non-stationary if the ADF test probability value is greater than 5% (Nurfajriyah et al., 2024). If the data is found to be non-stationary, it must be transformed into a stationary form through differencing, which involves subtracting the data value of a given period from that of the previous period (Susanti & Adji, 2020).

ARIMA Modeling

The ARIMA (Auto Regressive Integrated Moving Average) model is derived from a combination of parameters (p, d, q), where each parameter represents the Autoregressive (AR), Integrated (I), and Moving Average (MA) components. Parameter p indicates the order of the autoregressive (AR) model, d refers to the number of differencing steps required to achieve stationarity, and q denotes the order of the moving average (MA) model. In this stage, the values for p and q are determined using the autocorrelation function (ACF) and partial autocorrelation function (PACF) (Muis & Setiyadi, 2020).

Model Analysis

After selecting potential models based on the values of the autocorrelation function (ACF) and partial autocorrelation function (PACF), the models are tested and analyzed to determine the most suitable ARIMA model. The selection of the best ARIMA model is based on parameter estimation, specifically by identifying the model with the lowest values of the standard error of regression (S.E.), Akaike Information Criterion (AIC), and Schwarz Information Criterion (SIC) (Kaur et al., 2023; Zhu & Wei, 2013). Once the optimal model is identified, a residual diagnostic test is conducted to ensure that the residuals are free from autocorrelation. The absence of autocorrelation in the residuals indicates that the model has effectively captured all patterns within the data, thereby improving the accuracy of predictions (Aznarte et al., 2010). After the model passes the diagnostic tests, it undergoes further validation to assess its accuracy in predicting stock prices by comparing its forecasted values to actual observed data.

Model Evaluation

The model evaluation stage aims to identify the best model for forecasting stock prices. This selection is performed after conducting a white noise test as part of the diagnostic evaluation (Mustapa & Ismail, 2019). To determine the most appropriate ARIMA model, specific criteria are applied, including the lowest values of the standard error of regression (S.E.), Akaike Information Criterion (AIC), and Schwarz Information Criterion (SIC).

Stock Price Forecasting

Forecasting involves predicting future events or trends. Forecasting can be categorized into three types: short-term, medium-term, and long-term. Short-term forecasting typically projects events over a few time periods, such as days, weeks, or months. Medium-term forecasting covers a period of one to two years, while long-term forecasting spans several years into the future (Devita et al., 2021; Montgomery et al., 2017). In this study, stock price modeling and forecasting are conducted as a short-term analysis covering a 12-month period from December 27, 2023, to December 24, 2024. Additionally, the forecasting process includes predicting the closing price of ADRO shares for 10 days beyond the last recorded data.

Analysis and Discussion

Data Collection

This study utilizes a dataset comprising 238 observations covering the period from December 27, 2023, to December 24, 2024. It is important to note that daily stock price data is only available on weekdays, as stock trading is conducted five days a week. Consequently, stock price data is not recorded on weekends and national holidays. This factor must be considered in the analysis to prevent potential bias arising from missing data on specific days. The movement of ADRO stock prices during this period is illustrated in the following figure:

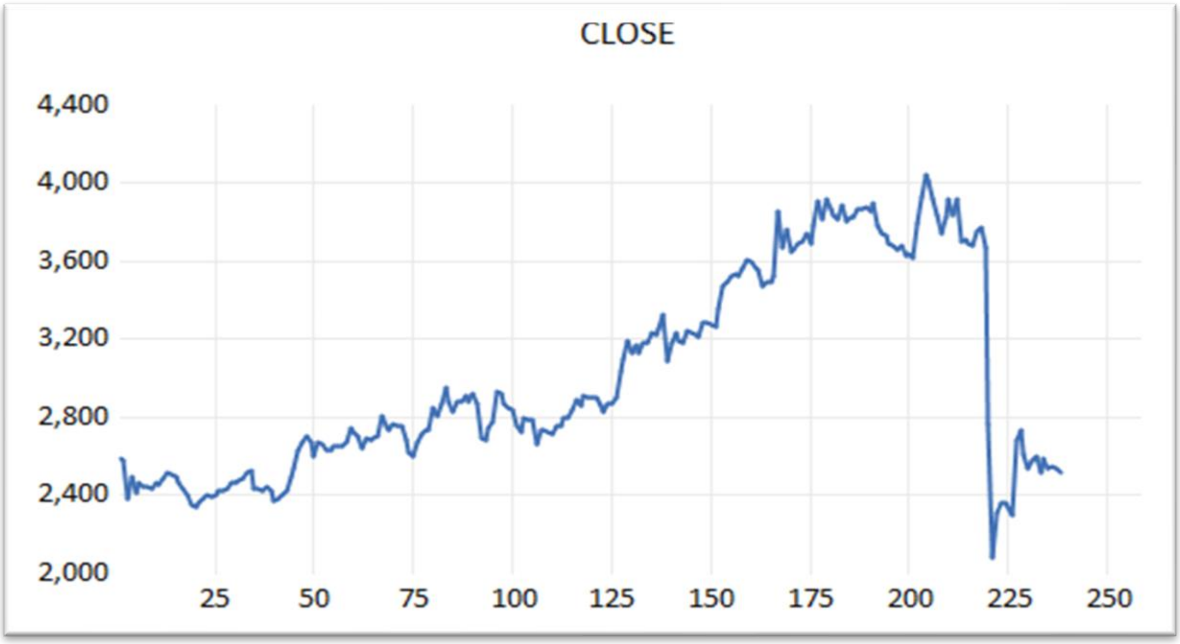

Figure 1. ADRO stock value graph plot

The ADRO stock price graph indicates a general upward trend; however, a sharp decline occurred at the end of November 2024. This decline was attributed to the spinoff of PT Adaro Andalan Indonesia Tbk (AAID), which shifted its focus entirely to the coal energy sector. According to Bareksa's analysis on December 4, 2024, ADRO shares dropped by 2.12%, reaching IDR 2,310 during the first trading session on Wednesday (12/4). Over the past week, shares owned by conglomerate Garibaldi "Boy" Thohir have declined by approximately 16.3%, while over the past month, they have decreased by 41.22%. This downturn is believed to be associated with a potential decrease in ADRO's stock valuation following the AAID spinoff. Generally, holding companies are valued at approximately 50% of their total asset value. With the AAID spinoff, ADRO's assets have been reduced, leaving only its mining services, logistics, and renewable energy development plans.

Stationarity Test

An initial stationarity test was conducted using the Augmented Dickey-Fuller (ADF) test on the original ADRO stock price data. The results indicated that the data was not stationary at its original level. To address this issue, the first step involved applying a logarithmic transformation to the data.

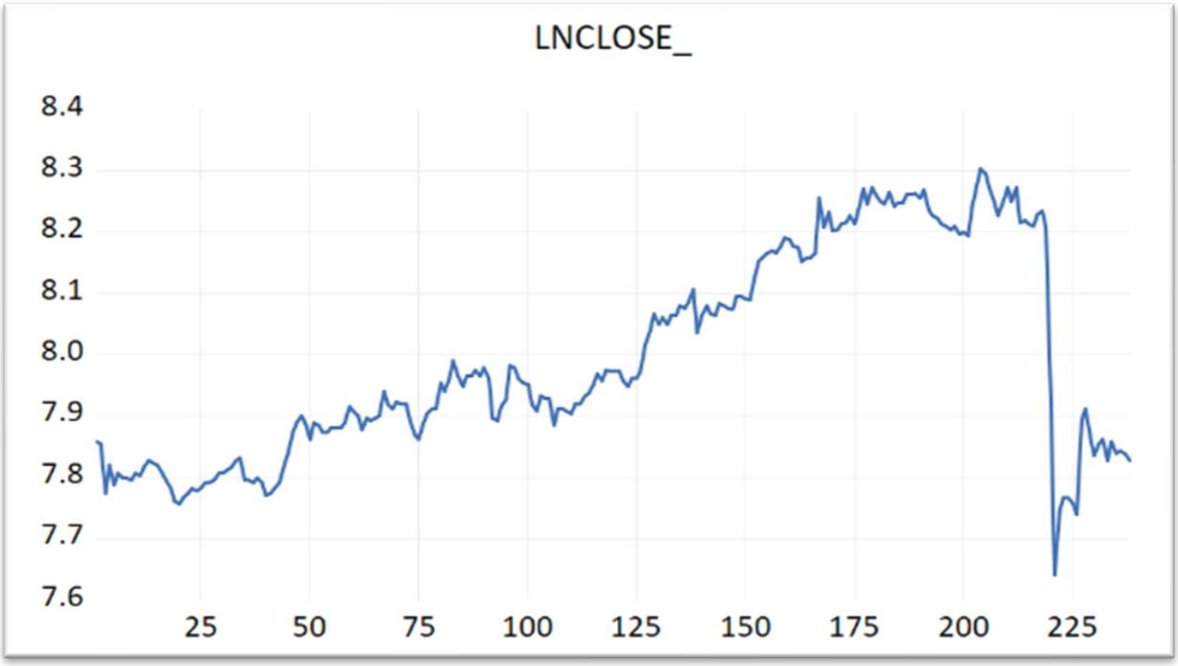

Figure 2. Log data transformation graph plot

However, the log-transformed data remained non-stationary, as indicated by a probability value exceeding 0.05. To resolve this, a first-order differencing method was applied. The unit root test, conducted using the ADF test in EViews, confirmed that the first-differenced data achieved stationarity, with an ADF probability value below 0.05 (5%). Therefore, in the ARIMA analysis, the first-differenced data will be utilized to construct the optimal model. The differencing process was performed on the logarithmized stock price data (dlnclose), as it exhibited better statistical properties compared to differencing the raw stock price data.

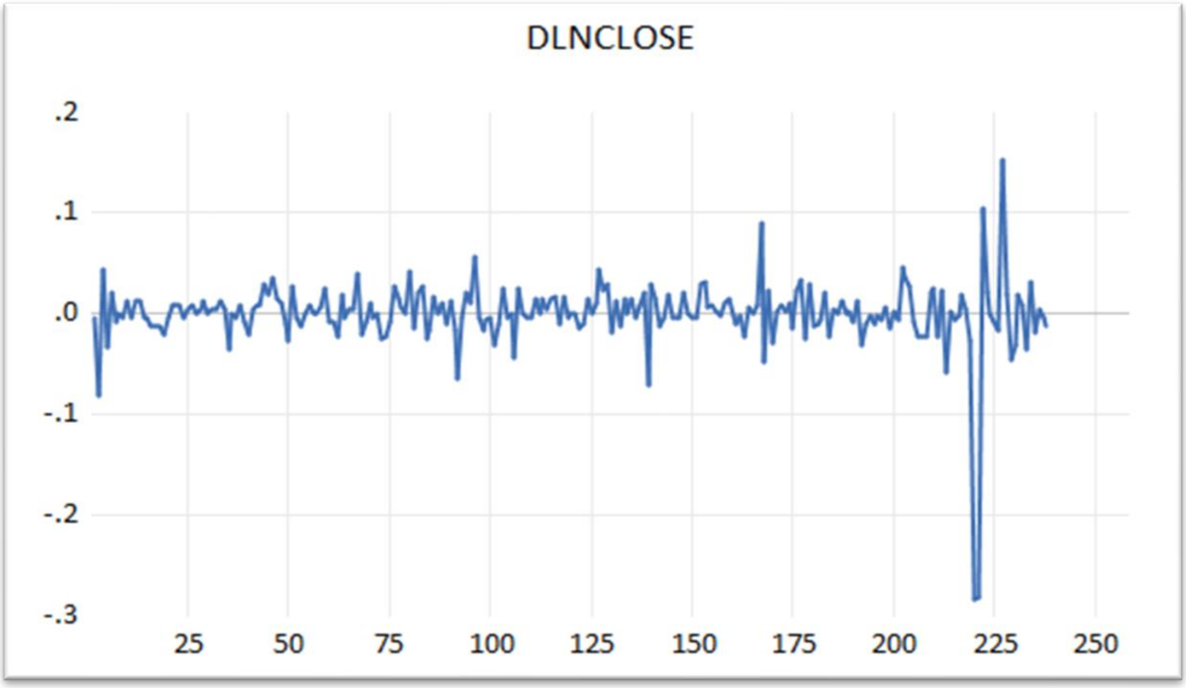

Figure 3. First-differenced data plot

From the first-order differencing of the log-transformed closing price data, the resulting graph is presented in Figure 3. Although the graph does not fully converge to zero, the overall data can be considered stationary. This suggests that the data pattern has undergone changes that reduce irregular trends and fluctuations, making it more suitable for time series analysis. This conclusion is further supported by the results of the Augmented Dickey-Fuller (ADF) test, which yielded a probability value of 0.0000, indicating statistical significance at the <0.05 level. This result confirms that the data meets the stationarity requirement, a critical assumption for applying the ARIMA model. A detailed summary of the stationarity test results is presented in the table below:

Table 2. Stationarity test results (ADF Test)

ADRO Model Data	ADF Test Probability
Close (Level)	0,3861
Close (Log)	0,3409
Diff. 1 Close (Log)	0,0000

ARIMA Modeling

After confirming that the data achieves stationarity at the first-differenced level (dlnclose), the next step involves selecting the appropriate ARIMA model for the analysis. This process requires identifying model parameter values by examining the patterns in the Partial Autocorrelation Function (PACF) and Autocorrelation Function (ACF) plots, as illustrated in the Correlogram. This analysis facilitates the determination of optimal values for the Auto-Regressive (AR) and Moving Average (MA) parameters, ensuring that the selected model effectively represents the data. The corresponding correlogram is depicted in the following figure:

Date: 12/31/24 Time: 13:43
Sample (adjusted): 2 238
Included observations: 237 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.162	0.162	6.2716	0.012
		2	-0.109	-0.139	9.1533	0.010
		3	-0.088	-0.047	11.015	0.012
		4	-0.016	-0.008	11.079	0.026
		5	0.075	0.066	12.456	0.029
		6	-0.143	-0.184	17.461	0.008
		7	-0.105	-0.035	20.164	0.005
		8	0.047	0.049	20.712	0.008
		9	0.043	-0.009	21.169	0.012
		10	0.009	-0.013	21.189	0.020
		11	-0.109	-0.083	24.165	0.012
		12	0.042	0.076	24.603	0.017
		13	0.077	0.005	26.085	0.017
		14	0.024	0.016	26.232	0.024
		15	0.035	0.055	26.546	0.033
		16	-0.026	-0.014	26.725	0.045
		17	-0.022	-0.044	26.852	0.060
		18	-0.052	-0.048	27.552	0.069
		19	-0.013	0.034	27.594	0.092
		20	0.016	-0.004	27.665	0.118

Figure 4. The correlogram of dlnclose

Based on the significant lags observed in the figure, the model estimates follow the general ARIMA (*p*, *d*, *q*) structure, where:

1) *p* represents the number of lags in the autoregressive (AR) component,
2) *d* indicates the degree of differencing required to achieve stationarity, and

3) *q* denotes the number of lags in the moving average (MA) component.

Considering the identified patterns in the graph, the proposed model specifications are summarized in the table below:

Table 3. ARIMA model estimates

ADRO Model Data	ARIMA Specification
Diff. 1 Close (Log)	ARIMA (1,1,0)
	ARIMA (0,1,1)
	ARIMA (1,1,1)
	ARIMA (2,1,0)
	ARIMA (2,1,1)

Model Analysis

After identifying potential models based on the ACF and PACF values, the next step involves testing and analyzing these models to determine the most suitable one. The selection of the optimal ARIMA model is based on minimizing key statistical criteria, including Standard Error of Regression (SSE), Akaike Information Criterion (AIC), and Schwarz Criterion (SIC).

Once the best-fitting model is identified, a residual diagnostic test is conducted to assess whether the residuals exhibit autocorrelation. The absence of autocorrelation in the residuals suggests that the model effectively captures the underlying data patterns, thereby enhancing the accuracy of the forecasts. The parameter estimates for model evaluation are provided in the following table:

Table 4. Statistical test results for model parameter estimation

Model	Significant Parameters	SSE	AIC	SIC	Residuals
ARIMA (1,1,0)	✓	0.035005	-3.853980	-3.810080	×
ARIMA (0,1,1)	✓	0.034872	-3.861513	-3.817613	×
ARIMA (1,1,1)	✓	0.034823	-3.860076	-3.801543	✓
ARIMA (2,1,0)	✓	**0.034732**	**-3.865322**	**-3.806789**	✓
ARIMA (2,1,1)	×	0.030937	-0.858934	-3.785769	✓

Model Evaluation

Based on the statistical test results presented in Table 4, the ARIMA (2,1,0), ARIMA (1,1,1), and ARIMA (2,1,1) models show no signs of autocorrelation. Among these models, the ARIMA (2,1,0) model exhibits the lowest SSE, AIC, and SIC values, indicating that it is the most efficient. Therefore, the ARIMA (2,1,0) model is selected as the best model for analysis and will be used for forecasting over the next 20 periods. By selecting an optimal model, it is expected that the forecasting results will be more accurate and provide better insights for decision-making.

Stock Price Forecasting

In this study, short-term stock price forecasting is conducted for the next 20 periods using training data collected from December 27, 2023, to December 24, 2024. The selected model, ARIMA (2,1,0), is employed to predict the closing prices of ADRO stock. The forecasted closing prices for the 20 periods are presented in Table 5 below:

Table 5. Forecasted ADRO stock price

No.	Close Price	No.	Close Price
1.	2505.714	11.	2507.811
2.	2508.928	12.	2507.603
3.	2509.924	13.	2507.396
4.	2509.455	14.	2507.188
5.	2509.029	15.	2506.980
6.	2508.818	16.	2506.773
7.	2508.640	17.	2506.565
8.	2508.439	18.	2506.357
9.	2508.228	19.	2506.150
10.	2508.018	20.	2505.942

Next, Figure 5 presents a combined graph of actual and predicted stock prices. From the graph, it is evident that the forecasted values closely follow the volatility patterns observed in stock price movements. Despite significant fluctuations in the actual stock prices, the model effectively preserves the overall trend, indicating that the predictions remain relevant to market dynamics. This suggests that even during periods of sharp price movements, the applied model can adequately capture stock price behavior. Consequently, this model provides a relatively accurate projection of future stock price trends, serving as a valuable tool for investors in making well-informed investment decisions.

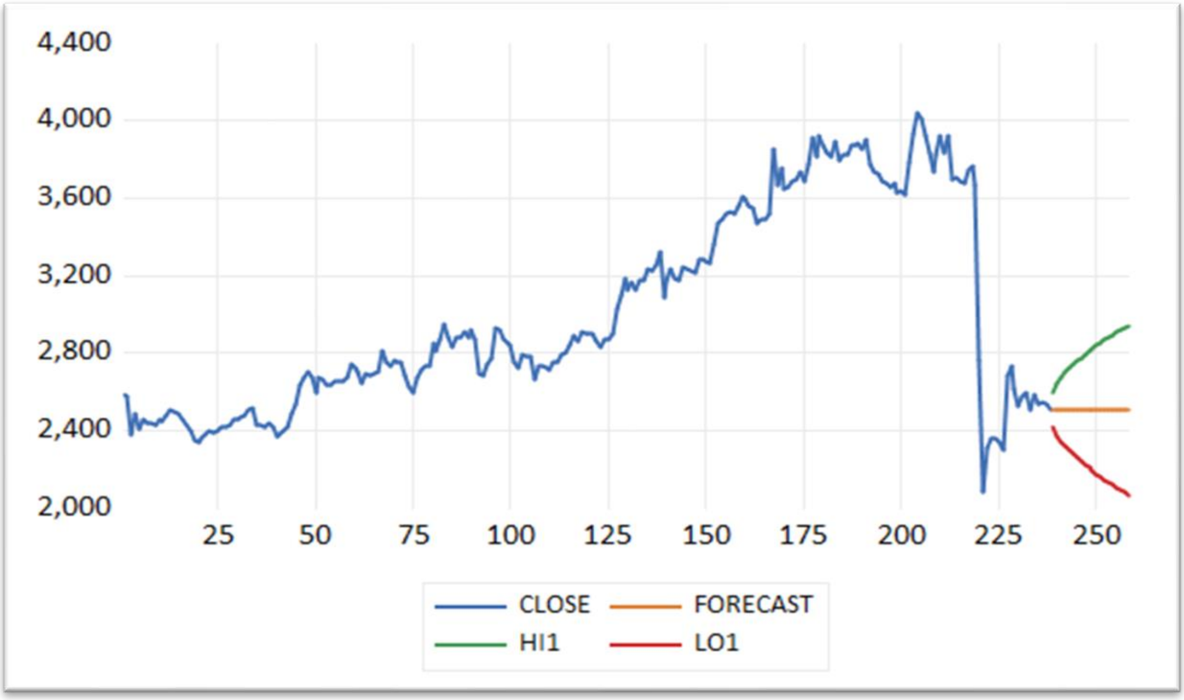

Figure 5. The graph of ADRO forecasting plot

Conclusion

This study employs the ARIMA (2,1,0) model to forecast ADRO stock prices using 238 historical data points collected from December 27, 2023, to December 24, 2024. The forecasting results demonstrate that the ARIMA model effectively captures stock price dynamics, with predictions closely aligning with historical trends. This confirms the model's capability in identifying recurring patterns and maintaining stable long-term forecasts. However, certain limitations in applying the ARIMA model have been identified. One major limitation is its high dependence on the quality of historical data, as data imperfections can impact prediction accuracy. Additionally, the stationarity assumption underlying the model requires further validation to ensure the data meets the necessary conditions before modeling.

To enhance forecasting accuracy, future research could explore hybrid approaches by integrating ARIMA with machine learning techniques. Machine learning methods can improve predictive performance by identifying complex and nonlinear patterns that may not be fully captured by the ARIMA model alone. By combining these methods, future stock price forecasting can become more adaptive and responsive to rapid market changes. This integrated approach is expected to yield more precise and insightful results for stock market analysis. Furthermore, the combination of ARIMA and machine learning has the potential to make a significant contribution to investment decision-making, particularly for investors who rely on accurate and data-driven predictions. It is anticipated that this hybrid approach will open new avenues in financial market research, providing more robust tools for understanding and forecasting stock price movements.

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