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PT Hexindo Adiperkasa TBK Stock Price Prediction for 2026-2027 Using the Autoregressive Integrated Moving Average (ARIMA) Method

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Abstract. *This study aims to predict the stock price of PT Hexindo Adiperkasa Tbk, listed under the ticker symbol HEXA, using the Autoregressive Integrated Moving Average (ARIMA) method in RStudio. The data used consist of monthly HEXA stock prices. Historical data from January 2021 to April 2025 were used as the model training dataset, while actual data from May 2025 to April 2026 were used as a benchmark for evaluating prediction results. The main forecasting period in this study covers May 2026 to December 2027. The research stages include data pattern identification, the Augmented Dickey-Fuller (ADF) stationarity test, differencing, ACF and PACF analysis, model selection based on AIC and BIC, parameter significance testing, diagnostic checking using the Ljung-Box test and Q-Q Plot, and accuracy measurement using MAPE, MAE, and RMSE. Based on the RStudio output, the best model is ARIMA (0,2,1), with an AIC value of 753.2217 and a BIC value of 757.0457. The accuracy results during the comparison period indicate a MAPE of 5.26%, an MAE of 268.67, and an RMSE of 398.31. The main forecasting results show that the HEXA stock price is predicted to reach 4,400 in May 2026 and 3,947 in December 2027. Although the MAPE value during the comparison period falls into the very good category according to the output table, the findings should still be interpreted cautiously because the Q-Q Plot indicates deviations in the tails of the residual distribution, and the prediction interval becomes wider over a longer forecasting horizon.*

Keywords: *Stock Price; HEXA; ARIMA; Stock Forecasting; RStudio*

JEL Classification: *C53, C58, G11, G17*

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INTRODUCTION

The capital market is an important component in the financial system because it functions as a means of intermediation between investors who have excess funds and issuers who need funding (Woodford, 2010; Allen et al., 2013; Véron & Wolff, 2016). In the capital market, shares are an investment instrument that is in great demand because it provides profit opportunities through capital gains and dividends (Nukala & Prasada, 2021; Hicham et al., 2024). Investor behavior in choosing shares cannot be separated from risk perceptions, expected returns, and market conditions that change from time to time. Nisani et al. (2022), Saranj & Zolfaghari (2025);

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Naseem et al. (2021); Parveen et al. (2023) explain that individual investor behavior can change following conditions of market uncertainty, including in the period before and during the pandemic.

The development of the Indonesian capital market also shows that stock prices can react to certain information and events. Agatón et al. (2024), Maddodi & Kunte (2024), Meyer et al. (2022) shows that the capital market can respond to an event through changes in market indicators. Piero & Natsir (2023) also show that external events can influence the movement of certain company shares. These findings show that stock prices do not stand alone, but are related to information received and interpreted by investors (Cornell et al., 2017; Hirshleifer et al., 2011; Sprenger et al., 2014; Seasholes & Zhu, 2010).

Apart from market information, macroeconomic factors can also influence stock price dynamics. Fauziah et al. (2015) show that there is a dynamic relationship between interest rates and stock prices in Indonesia. Nugraha & Wirama (2023) explain that exchange rates and inflation are related to stock returns. Sukri & Abundanti (2023) show that net foreign funds, gold prices and interest rates are related to JCI movements. Based on this description, stock price prediction needs to be understood as an analytical process in a complex market environment (Tuarob et al., 2021; Shah et al., 2019; Agrawal et al., 2025; Singh & Khushi, 2021; Gandhmal & Kumar, 2019; Teixeira & Barbosa, 2024).

In recent developments, stock price predictions are increasingly being carried out using a quantitative approach based on historical data. Alawiyah et al. (2024) apply the ARIMA method to predict the share price of PT XL Axiata Tbk. Ro'ifah (2024) uses ARIMA to predict the share price of PT Bank Rakyat Indonesia (Persero) Tbk. Zam et al. (2025) apply ARIMA to the closing value of the Composite Stock Price Index. The use of this method shows that the time series approach is still relevant for estimating stock price movements and capital market indices.

The main problem in stock price prediction lies in the fluctuating nature of the data, which is not always stationary, and which is difficult to ascertain in a linear direction. Dewanti et al. (2024) used the SSA-ARIMA hybrid model to improve the stock price forecasting capabilities of PT Indofood Sukses Makmur Tbk. Zili et al. (2022) uses a hybrid ARIMA-GARCH model and the walk forward method because stock movements not only have an average pattern, but are also related to volatility. Fadhilah et al. (2024) apply ARIMA-GARCH to banking subsector stock returns to capture data movement patterns and instability.

The object of this research is PT Hexindo Adiperkasa Tbk with the stock code HEXA. This company operates in heavy equipment trading and after-sales services, and is linked to the mining, construction, forestry, plantation and equipment rental sectors. These characteristics make HEXA shares relevant for analysis because the heavy equipment sector is related to real economic activity and industrial equipment needs. In this article, the data used is HEXA's monthly share prices for the period January 2021 to April 2026, with training data from January 2021 to April 2025, actual comparison data from May 2025 to April 2026, and the main prediction period from May 2026 to December 2027.

The urgency of this research lies in the need to provide predictive information regarding the direction of HEXA share price movements based on historical data. Investors and parties interested in the capital market need analytical tools that can provide quantitative stock price estimates (Kumar et al., 2021; Grennan & Michaely, 2021; Lee et al., 2011; Abuselidze & Slobodianyk, 2021). Hamdani et al. (2025) emphasize the importance of measuring accuracy in forecasting Indonesian stock prices. Tirta et al. (2024) also show that individual stock price predictions can be used to support the market analysis process, although the prediction results must still be interpreted with caution.

The research gap in this research lies in the limited study of PT Hexindo Adiperkasa Tbk (HEXA) share price forecasting using ARIMA with performance evaluation on actual data outside

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the training period, namely using the actual comparison period before preparing the main forecast. Previous studies mostly discussed other objects, such as Dewanti et al. (2024) on Indofood shares, Ro'ifah (2024) on BRI shares, Paidi et al. (2024) on ANTM shares, and Markus et al. (2025) on shares in the LQ45 index. In fact, HEXA is interesting to study because it operates in the heavy equipment sector related to mining, construction, forestry and plantations. In addition, research data shows price fluctuations and a decline phase approaching 2025. Based on this description, this research emphasizes the application of ARIMA to HEXA shares through out-of-sample evaluation before being used to forecast the 2026–2027 period.

The novelty of this research lies in applying a systematic ARIMA evaluation design to HEXA shares, by separating the data into a training period, an actual comparison period, and a main forecasting period (Nensi et al., 2025; Ansari & Alam, 2024). Through this scheme, the model is not directly used to forecast the 2026–2027 period, but is first evaluated using actual data from May 2025 to April 2026. The contribution of this research lies in the integration of the stages of model selection, diagnostic checking, and accuracy evaluation in one measurable HEXA share price forecasting procedure.

The aim of this research is to predict the share price of PT Hexindo Adiperkasa Tbk with the stock code HEXA for the period May 2026 to December 2027 using the Autoregressive Integrated Moving Average (ARIMA) method. Specifically, this research aims to identify monthly HEXA stock price data patterns, test data stationarity, determine the best ARIMA model, evaluate model residuals, measure prediction accuracy, and present forecasting results as supporting information in investment analysis.

Stocks, Stock Prices and Stock Price Predictions

Shares are a capital market instrument that shows investor ownership of a company. In the investment context, share prices are important information because they reflect the market's assessment of the company's prospects, risks, and investors' expectations of returns. Stock price movements are dynamic so analysis based on historical data is needed to help investors predict the direction of price changes. Alawiyah et al. (2024) explain that the financial market is a dynamic and uncertain sector so stock price predictions can be used as a tool in reading price movement patterns.

In this research, the main variable analyzed is the monthly share price of PT Hexindo Adiperkasa Tbk with the share code HEXA. Therefore, the approach used is not to test the causal influence between fundamental variables, but rather to model historical patterns of stock prices over time. Simanjuntak et al. (2023) emphasize that stock price modeling can be used to help investors choose stocks based on the model's ability to capture data patterns. Thus, HEXA stock price predictions in this research are placed as quantitative technical analysis that utilizes past information to estimate future value.

Time Series Data and Stationarity

Time series data is data that is arranged based on time sequence so that each observation is related to a certain observation period. In this research, the time series data is in the form of monthly HEXA stock prices from January 2021 to April 2026. The ARIMA model requires stationary data, namely data that has a relatively stable mean and variance throughout the observation period. Zam et al. (2025) stated that the ARIMA stages on capital market data include data exploration, ADF stationarity test, differencing process, identification of ACF and PACF, and selection of the best model.

Stationarity in the average can be tested using Augmented Dickey-Fuller (ADF). The hypothesis used is as follows.

H0: $\delta = 0$, the data has a unit root or is not stationary.

H1: $\delta < 0$, the data does not have a unit root or is stationary.

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$$t_{count} = \hat{\delta} / SE(\hat{\delta})$$

Note: $\hat{\delta}$ is the estimated parameter in the ADF equation, while $SE(\hat{\delta})$ is the standard error of the estimated parameter. If the p-value is smaller than the significance level, then H0 is rejected and the data is declared stationary. If the data is not yet stationary on average, a differencing process is carried out to eliminate trends or systematic patterns that cause non-stationarity. With the backward shift operator B, the d-order differencing process can be written as follows.

$$\Delta^d P_t = (1 - B)^d P_t$$

Information: P_t is the stock price in period t, B is the backward shift operator, d is the order of differencing, and Δ^d P_t is the stock price data after differencing of the dth order. Fadhilah et al. (2024) shows that in fluctuating stock data, checking the characteristics of the time series needs to be carried out before the forecasting model is established. Because this research uses ARIMA without exogenous variables, the success of the differencing process is an important basis before determining the AR and MA components.

Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF)

After the data is stationary, the next stage is to identify autocorrelation patterns through the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). ACF is used to see the relationship between data in the current period and data in the previous lag. PACF is used to see the partial relationship between current period data and a certain lag after the influence of intermediate lags is removed. In ARIMA research on IHSG, Zam et al. (2025) used ACF and PACF as the basis for identifying model candidates after the data was made stationary.

$$\hat{\rho}_k = \hat{\gamma}_k / \hat{\gamma}_0 = \Sigma(P_t - \bar{P})(P_{t+k} - \bar{P}) / \Sigma(P_t - \bar{P})^2$$

Information: ρ̂_k is the autocorrelation estimate at the kth lag, γ̂_k is the autocovariance estimate at the kth lag, γ̂_0 is the variance estimate, P_t is the stock price in period t, P̄ is the average stock price, and n is the number of observations. Practically speaking, the ACF pattern helps identify the MA(q) order, while the PACF pattern helps identify the AR(p) order. However, selecting the final model is not enough just based on the ACF and PACF visual patterns, but needs to be followed by comparing models using information criteria and diagnostic tests.

Autoregressive Integrated Moving Average (ARIMA) Model

ARIMA is a time series forecasting model that combines three main components, namely autoregressive (AR), integrated (I), and moving average (MA). The AR component shows the dependence of current values on past values. Component I shows the number of differencing processes carried out so that the data becomes stationary. The MA component shows the influence of past errors or residuals on current values. Alawiyah et al. (2024) used ARIMA to predict the share price of PT XL Axiata Tbk and obtained the best ARIMA (2,1,2) model. In general, the ARIMA(p,d,q) model can be written as follows.

$$\varphi_p(B)(1 - B)^d P_t = c + \theta q(B)\varepsilon_t$$

Note: φ_p(B) is an autoregressive operator of order p, θ_q(B) is a moving average operator of order q, d is differencing order, c is a constant, and ε_t is the residual in period t.

ARIMA Model Selection

ARIMA model selection is carried out by comparing several candidate models based on information criteria. Two commonly used measures are the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). Smaller AIC and BIC values indicate that the model has a better balance between model accuracy and number of parameters. Dewanti et al. (2024)

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uses the SSA-ARIMA approach in forecasting the share price of PT Indofood Sukses Makmur Tbk and places model selection as an important part of the forecasting procedure.

$$AIC = -2\ln(L) + 2k$$

$$BIC = -2\ln(L) + k\ln(n)$$

Note: L is the likelihood value of the model, k is the number of parameters, and n is the number of observations.

Diagnostic Checking Residuals and Prediction Accuracy

After the ARIMA model is selected, the next stage is diagnostic checking residuals. A good model residual should be white noise, that is, it should not have significant autocorrelation. The Ljung-Box test can be used to check whether the residuals still contain autocorrelation. Fadhilah et al. (2024) emphasize that in stock data, examining residuals is important because data volatility and instability can affect the quality of the forecasting model.

$$Q = n(n + 2)\Sigma[\hat{\rho}_k^2 / (n - k)]$$

Note: Q is the Ljung-Box statistic, n is the number of observations, m is the number of lags tested, and ρ̂_k is the residual autocorrelation at the kth lag. Prediction accuracy in this study was assessed using Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). MAPE shows the average percentage of absolute error, MAE shows the average absolute error in stock price units, while RMSE provides a larger penalty for large prediction errors. Ishlah et al. (2023) and Fitri et al. (2023) use a prediction error measure to assess the model's ability to forecast stock data or stock indices.

$$MAPE = (100\% / n)\Sigma\,|(P_t - F_t) / P_t|$$

$$MAE = (1 / n)\Sigma\,|P_t - F_t|$$

$$RMSE = \sqrt{[(1 / n)\Sigma(P_t - F_t)^2]}$$

Note: P T is the actual value, F N is the predicted value, and n is the number of observations in the comparison period.

Research Thinking Framework

The rationale for this research starts from HEXA's monthly stock price data which is arranged as a time series. The data was tested for stationarity using ADF. If the data is not stationary, differencing is carried out until the data meets the stationarity assumption. After that, the ACF and PACF patterns are used to help form candidate ARIMA models. Candidate models are compared using AIC and BIC, then the best model is tested through parameter significance and residual diagnostic checking. Models that meet the criteria are used to calculate prediction accuracy with MAPE, MAE, and RMSE, then applied to forecast HEXA share prices for the period May 2026 to December 2027.

Based on this flow, research work assumptions can be formulated that the historical pattern of HEXA share prices can be modeled using ARIMA after the data is made stationary. The next work estimate is that the best ARIMA model that meets the criteria for model selection, parameter testing, diagnostic checking, and accuracy measures can be used as a tool to predict HEXA stock prices. Abbas et al. (2024) show that stock price predictions based on historical data can also be done using a deep learning approach, while Tarape & Yusuf (2025) show that stock prices remain sensitive to macroeconomic factors. Based on this description, ARIMA in this

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research is positioned as a predictive model based on historical patterns, not as a model that explains all the causes of changes in stock prices.

METHODS

The object of research is the share price of PT Hexindo Adiperkasa Tbk with the share code HEXA. The data used is secondary data on monthly share prices obtained from investing.com. The clean data used is 64 monthly stock price observations from January 2021 to April 2026. The model training data is 52 observations, namely from January 2021 to April 2025. The actual comparison data covers May 2025 to April 2026, while the main prediction period is May 2026 to December 2027. Monthly data were selected in preference to daily or weekly data for several methodological reasons. Monthly price data captures medium-term trends in HEXA share price movements, which are more consistent with the cyclical patterns of the heavy equipment sector tied to mining, construction, and plantation activities. While daily data could offer more granular observations, such frequency often introduces excessive noise from short-term market microstructure effects that ARIMA models are not designed to distinguish from genuine trend signals. Monthly aggregation also reduces the influence of temporary liquidity-driven price distortions and aligns with the reporting cycles commonly associated with the underlying economic sectors. Although the use of monthly data may limit the model's sensitivity to sudden short-term price movements, this trade-off is considered appropriate given the study's focus on medium-term price trend estimation for the 2026–2027 forecasting period. Before proceeding to model estimation, a data cleaning process was performed to ensure the quality and integrity of the time series. The raw data retrieved from investing.com were first inspected for duplicate date entries and non-parseable date formats, both of which were removed using date-based filtering functions in R. Each row was validated to contain exactly one observation per calendar month, and any rows with missing or non-numeric price values were excluded. Abnormal price movements were also visually checked using a time series plot to identify any implausible values; no observations required removal on these grounds. The dataset did not contain stock splits within the January 2021 to April 2026 observation period that would necessitate retroactive price adjustment, as confirmed through cross-referencing with corporate actions data on the source platform. After cleaning, the dataset comprised 64 valid monthly closing price observations, sequentially ordered without gaps, confirming the completeness of the time series before model estimation.

The analysis was implemented in RStudio through a structured procedure consisting of three sequential analytical stages. In the first stage, the required R packages (readxl, dplyr, lubridate, forecast, tseries, lmtest, ggplot2, writexl, and scales) were loaded, the data file was specified, and the period boundaries were defined, covering the training period (January 2021–April 2025), the actual comparison period (May 2025–April 2026), and the main forecast period (May 2026–December 2027). In the second stage, the raw data were parsed and cleaned by extracting the date and closing price columns, converting date strings to a standard format, and filtering out any rows with missing or non-numeric values. The cleaned data were then separated into a training subset (January 2021–April 2025) and an actual comparison subset (May 2025–April 2026). The training data were converted into a monthly time series object with a frequency of 12. Stationarity was then assessed using the Augmented Dickey-Fuller (ADF) test, and differencing was applied iteratively until the ADF p-value dropped below 0.05, subject to a maximum differencing order of d = 2. In the third stage, candidate ARIMA models were generated by systematically varying p and q from 0 to 3, with d fixed at the value determined in the preceding stage. Each candidate model was estimated using maximum likelihood (ML), and its AIC, BIC, and validation accuracy metrics (MAPE, MAE, and RMSE) were recorded. The model yielding the lowest AIC and BIC was selected as the best-fitting model. Residual diagnostics were subsequently performed using the Ljung-Box test and Q-Q Plot. The selected model was then applied to generate forecasts from May 2025 to December 2027, enabling both the comparison-period evaluation (May 2025–April 2026) and the main forecast for the target period (May 2026–

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December 2027). The RStudio output comprised a clean data table, ADF test table, model comparison table, parameter significance table, Ljung-Box test table, accuracy table, actual-versus-predicted comparison table, and forecast table, together with time series plots, ACF-PACF plots, residual diagnostic plots, a Q-Q Plot, and a forecast graph. The complete RStudio scripts used in this study are provided as supplementary material.

RESULTS AND DISCUSSION

Description of HEXA Share Price Data

The training historical data shows the HEXA stock price moving from 3,270 in January 2021 to 4,710 in April 2025. In the training data, the lowest price was 3,270 and the highest price was 6,700. In complete data until April 2026, the lowest price remains 3,270 and the highest price remains 6,700. These figures show large increases in some periods, but there is also a clear decline phase towards 2025.

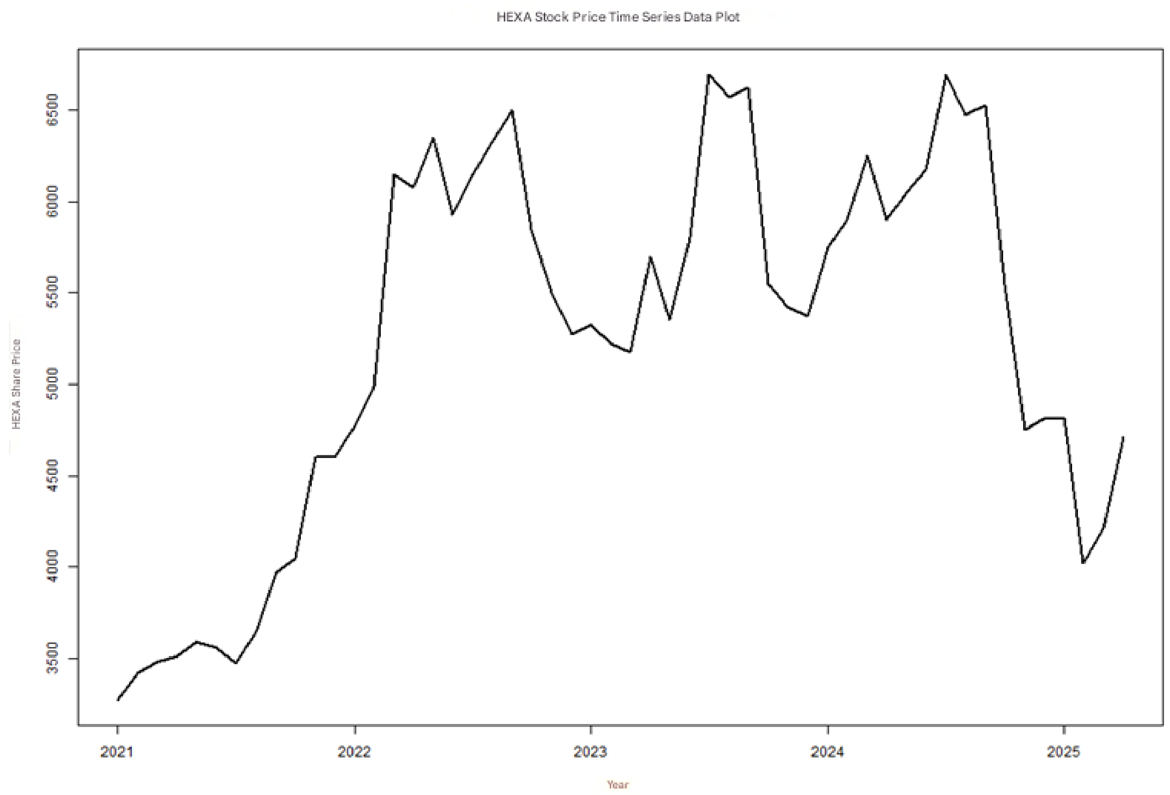

Figure 1. Time Series Data Plot of HEXA Share Prices

Source: RStudio Output, Processed by Researchers.

Figure 1 shows the HEXA share price pattern which is not constant throughout the observation period. Prices tend to increase from the beginning of 2021 until they reach a high level in 2022-2024, then experience a sharp decline from the end of 2024 to the beginning of 2025. This changing pattern is an initial indication that the data is not yet stationary at a level, so a formal stationarity test is needed.

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Descriptive Analysis

Table 1. Results of Descriptive Analysis of HEXA Share Prices

Descriptive Statistics	
Vars	1
N	64
Mean	5146,563
Sd	970,6081
Median	5250
Trimmed	5173,942
Mad	1045,233
Min	3270
Max	6700
Range	3430
Skew	-0,20389
Kurtosis	-1,02942
Se	121,326

Source: RStudio Output, Processed by Researchers.

Table 1 shows that HEXA share price data consists of 64 observations. The average share price was 5,146,563 with a median of 5,250, which indicates that share prices were in the range of around 5,000 during the observation period. The minimum value is 3,270 and the maximum value is 6,700, indicating that there is a fairly wide price range, namely 3,430. The standard deviation of 970.6081 also shows that the HEXA share price experienced quite large fluctuations. A skewness value of -0.20389 indicates that the data distribution is slightly skewed to the left, while kurtosis of -1.02942 indicates that the data distribution is relatively flat. In general, the results of these descriptive statistics show that HEXA's share price is fluctuating so it is relevant to analyze using the ARIMA time series method.

ADF Stationarity Test

Table 2. ADF Stationarity Test Results for HEXA Share Prices

Differencing	P-Value	Decision	Information
0	0,748536	Failed to Reject H0	Not stationary
1	0,054588	Failed to Reject H0	Not stationary
2	0,01	Reject H0	Stationary

Source: RStudio Output, Processed by Researchers.

Table 2 shows that the HEXA share price data is not yet stationary at the level because the p-value differencing 0 is 0.748536 which is greater than 0.05. After level 1 differencing, the p-value decreased to 0.054588, but was still greater than 0.05 so the data was not yet stationary. At level 2 differencing, the p-value becomes 0.01 or smaller than 0.05, so H0 is rejected. Thus, HEXA stock price data is declared stationary after level 2 differencing and the ARIMA model used has a differencing order of d = 2.

The use of second-order differencing (d = 2) in this study requires methodological clarification to address potential concerns about over-differencing. Over-differencing typically occurs when differencing is applied beyond what is necessary, which can artificially inflate model complexity or introduce spurious moving average components. In this study, d = 2 was not selected a priori but was determined empirically through a sequential ADF testing procedure. After first-order differencing, the ADF p-value of 0.0546 remained marginally above the 0.05

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significance threshold, indicating that the data had not yet achieved formal stationarity at d = 1. The application of second-order differencing reduced the p-value to 0.01, satisfying the stationarity criterion. This result is consistent with the behavior of stock price data that may exhibit persistent trend or near-unit-root characteristics even after a single round of differencing, particularly during periods that include structural shifts such as the sharp price decline observed toward the end of 2024. Additional evidence against over-differencing is provided by the Breusch-Pagan test result on the second-differenced series (p-value = 0.0902), which confirmed the absence of heteroscedasticity and thus the stability of variance. Furthermore, the Ljung-Box test on the residuals of the selected ARIMA (0,2,1) model yielded a p-value of 0.2731, confirming that the residuals qualify as white noise. This diagnostic outcome indicates that d = 2 did not result in model misspecification or excessive over-differencing. Taken together, these results support d = 2 as an empirically justified differencing order for the HEXA stock price series.

Differentiation Process

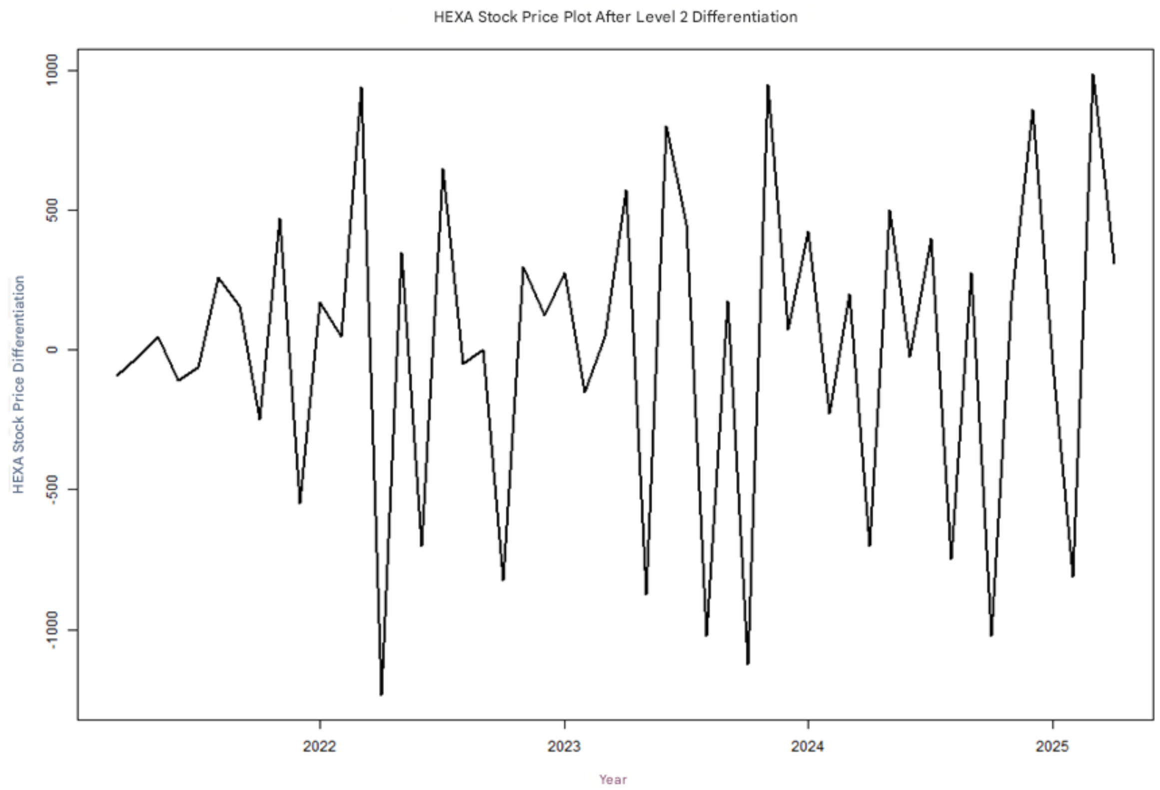

Figure 2. Plot of HEXA Stock Price After Level 2 Differentiation
Source: RStudio Output, Processed by Researchers.

Figure 2 shows the results of level 2 differencing. After differencing, the data fluctuates around the zero point with considerable amplitude. This fluctuation indicates that the trend element in the level data has diminished, but stock price changes still exhibit monthly volatility. Based on this description, the selection of an ARIMA model still requires support from the ACF, PACF, and AIC and BIC criteria.

Table 3. Breusch-Pagan Test Results

Differencing	BP Statistic	P-Value	Decision	Information
2	2,8708	0,0902	Failed to reject H0	There is no heteroscedasticity

Source: RStudio Output, Processed by Researchers.

Table 3 shows the p-value of the Breusch-Pagan test at 0.0902. Since this value is greater than 0.05, the test fails to reject H0. Based on the output, there is no indication of heteroscedasticity in the data after level 2 differencing. However, this test does not replace diagnostic checking of ARIMA residuals because the model residuals still need to be tested separately.

ACF and PACF Analysis

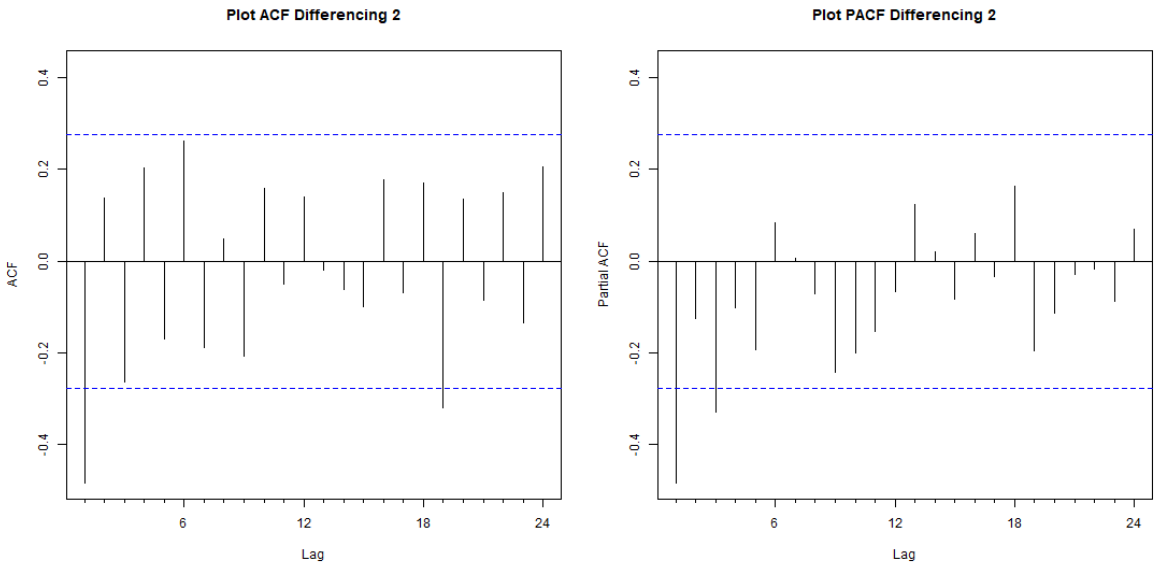

Figure 3. Plot of ACF and PACF After Level 2 Differentiation
Source: RStudio Output, Processed by Researchers.

Figure 3 shows the ACF and PACF patterns for data that has undergone level 2 differencing. In the ACF plot, lag 1 exhibits a significant negative spike that cuts off sharply, with subsequent lags falling within or near the significance bounds. This pattern is characteristic of a first-order Moving Average process, suggesting q = 1 as the primary candidate for the MA component. In the PACF plot, no single lag displays a dominant and clearly isolated spike with all subsequent lags firmly within the bounds, making identification of a strong pure AR order less straightforward. The PACF pattern instead shows a gradual decay or mild oscillation in the early lags, which, combined with the sharp ACF cutoff, further supports an MA-dominant structure. Based on these observations, ARIMA (0,2,1) emerges as the principal candidate from the visual analysis, with models incorporating low AR orders such as ARIMA (1,2,1) and ARIMA (3,2,1) also considered as supplementary candidates to accommodate possible residual autocorrelation in the PACF. The determination of the final model is thus based not only on the ACF and PACF visualizations, but also on a formal comparison of candidate models using AIC, BIC, and prediction validation results as presented in the following section.

Selection of the Best ARIMA Model Based on AIC and BIC

Table 4. Comparison of ARIMA Models for HEXA Stock Price

Model	AIC	BIC	MAE	MAPE (%)	RMSE
ARIMA (0,2,1)	753,2217	757,0457	268,72	5,27	398,33
ARIMA (1,2,3)	754,7198	764,2799	464,31	10,02	522,12
ARIMA (1,2,1)	754,7588	760,4948	350,43	7,29	413,72
ARIMA (2,2,2)	754,7959	764,3560	573,34	12,56	659,59
ARIMA (0,2,2)	754,8357	760,5718	318,89	6,54	395,45
ARIMA (0,2,3)	756,2046	763,8527	544,83	11,85	611,55
ARIMA (3,2,3)	756,2172	769,6013	440,46	9,25	531,68

ARIMA (2,2,1)	756,4770	764,1251	509,09	10,99	560,77
ARIMA (3,2,2)	756,6369	768,1091	444,79	9,57	501,90
ARIMA (1,2,2)	756,6878	764,3359	405,96	8,58	454,30
ARIMA (2,2,3)	756,7128	768,1849	481,57	10,43	543,15
ARIMA (3,2,1)	757,1056	766,6657	277,61	5,72	361,62
ARIMA (3,2,0)	762,0563	769,7044	1.006,99	22,34	1.208,93
ARIMA (1,2,0)	765,3625	769,1865	2.530,61	56,29	3.057,19
ARIMA (2,2,0)	766,2973	772,0334	1.755,11	39,25	2.176,42
ARIMA (0,2,0)	776,5288	778,4408	3.215,00	71,29	3.816,40

Source: RStudio Output, Processed by Researchers.

Based on Table 4, the ARIMA (0,2,1) model has the lowest AIC of 753.2217 and BIC of 757.0457. This model also has a validation MAPE of 5.27%, MAE of 268.72, and RMSE of 398.33 in the model comparison table. Although the ARIMA (3,2,1) model produces a lower RMSE value, ARIMA (0,2,1) is still selected as the main model because it has the smallest AIC and BIC values, and shows lower MAE and MAPE. The selection of ARIMA (0,2,1) over ARIMA (3,2,1) can be explained through three interconnected considerations. First, ARIMA (0,2,1) achieves the lowest AIC (753.2217) and BIC (757.0457) among all candidate models, whereas ARIMA (3,2,1) yields an AIC of 757.1056 and a BIC of 766.6657. The AIC and BIC penalize unnecessary parameters while rewarding goodness of fit, so the lower values of ARIMA (0,2,1) indicate a superior balance between model complexity and in-sample accuracy. Second, the principle of parsimony favors simpler models when predictive performance is comparable, as models with fewer parameters are less prone to overfitting. ARIMA (3,2,1) contains four estimated parameters (three AR terms and one MA term) compared to ARIMA (0,2,1) which contains only one (the MA term), making ARIMA (0,2,1) substantially more parsimonious. Third, ARIMA (0,2,1) yields a lower MAE (268.72 versus 277.61) and a lower MAPE (5.27% versus 5.72%) than ARIMA (3,2,1), demonstrating that its average predictive accuracy is not sacrificed by the simpler structure. The lower RMSE of ARIMA (3,2,1) suggests a better handling of isolated large errors, but RMSE is more sensitive to outlier periods and may not adequately represent overall predictive consistency. Because the mean-based metrics (MAE and MAPE) favor ARIMA (0,2,1), and the information criteria confirm its statistical efficiency, the selection of ARIMA (0,2,1) as the best model reflects a decision that integrates parsimony, information criteria, and overall predictive consistency rather than relying on any single error measure.

Parameter Significance Test

Table 5. Results of the ARIMA Model Parameter Significance Test (0,2,1)

Parameter	Estimate	Std. Error	Z-Value	P-Value	Information
ma1	-0,9502	0,0665	-14,2801	2,91E-46	Significant

Source: RStudio Output, Processed by Researchers.

Table 5 shows that the MA(1) or ma1 parameter has an estimate of -0.9502, a standard error of 0.0665, a z-value of -14.2801, and a p-value of 2.91E-46. Because the p-value is very small or less than 0.05, the ma1 parameter is declared significant. Thus, the first-order moving average component in the ARIMA (0,2,1) model has a statistical contribution to the formation of the model.

Diagnostic Checking Residual

Table 6. Results of the Ljung-Box Residual ARIMA Test (0,2,1)

Model	Lag	Fitdf	P-Value	Decision	Information
ARIMA (0,2,1)	12	1	0,2731	Failed to reject H0	Residual is white noise

Source: RStudio Output, Processed by Researchers.

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Table 6 shows the p-value of the Ljung-Box test of 0.2731 at lag 12 with fitdf 1. Because the p-value is greater than 0.05, the test decision is to fail to reject H0. Based on this output, the residuals of the ARIMA (0,2,1) model do not show significant autocorrelation and can be categorized as white noise.

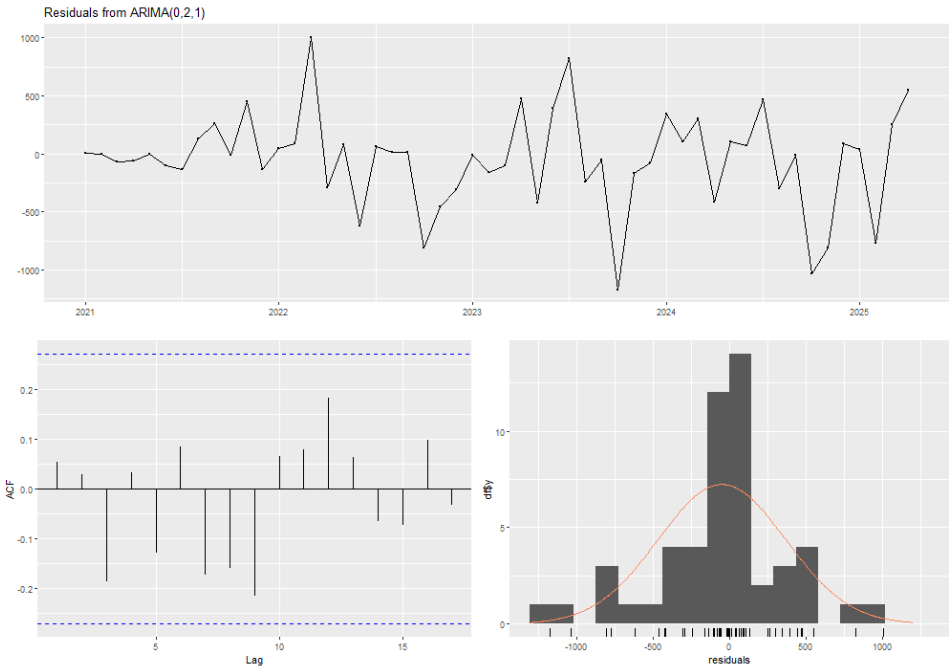

Figure 4. Diagnostic Residual Model ARIMA (0,2,1)
Source: RStudio Output, Processed by Researchers.

Figure 4 displays the residuals from the ARIMA(0,2,1) model, the residual ACF, and the residual histogram. Visually, the residuals still exhibit some fairly large spikes, but the residual ACF plot does not show any dominant autocorrelation beyond the significance level. This is consistent with the results of the Ljung-Box test, which indicates that the residuals are white noise.

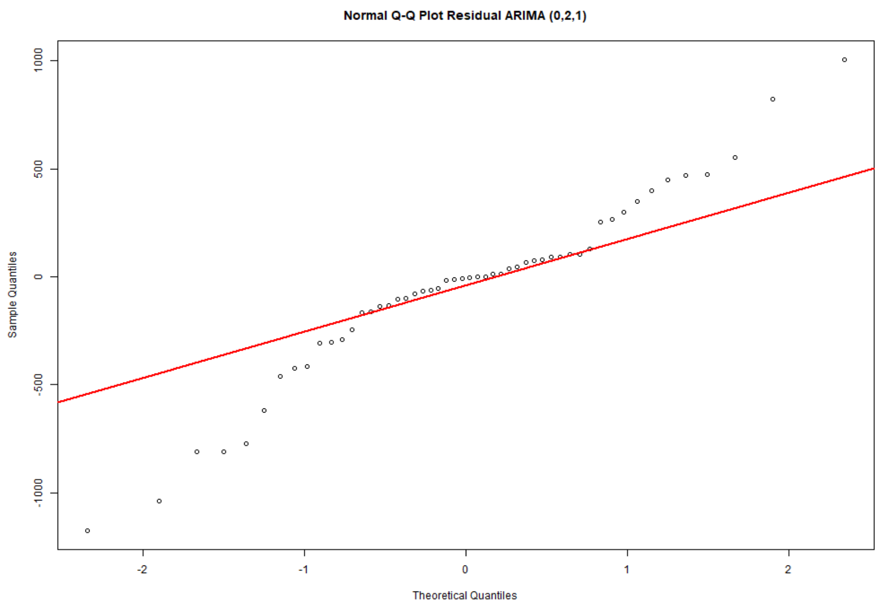

Figure 5. Normal Q-Q Plot of Residual ARIMA (0,2,1)
Source: RStudio Output, Processed by Researchers.

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Figure 5 shows that the residual points in the middle section follow the reference line relatively closely, but the points in the left and right tails deviate from the line. Because the output does not provide a formal normality test, the conclusion of normality cannot be statistically confirmed. Based on the Q-Q plot, the residuals do not fully follow a normal distribution, especially in the tails. This finding should be taken into account when interpreting prediction intervals.

Model Accuracy Using MAPE, MAE, and RMSE

Table 7. Accuracy of the ARIMA (0,2,1) Model in the Comparison Period

Type of Accuracy	Value	Information
MAPE	5,26%	Very good
MAE	268,67	Absolute error value
RMSE	398,31	Root mean square error

Source: RStudio output, processed by researchers

Table 7 shows that the model's MAPE is 5.26%, MAE is 268.67, and RMSE is 398.31. Based on the output obtained, the MAPE value is categorized as very good. However, conclusions about accuracy should not be separated from the characteristics of the residuals and the prediction horizon. An RMSE greater than the MAE indicates the presence of relatively large errors in the comparison period, especially when the prediction is compared to a specific actual spike. The MAPE value of 5.26% should be understood as the average absolute percentage error over the comparison period, not as a measure of error for each individual month. Therefore, a MAPE value below 8% indicates that the model has a low level of prediction error, on average. However, this does not necessarily mean that all monthly periods have errors below 8%. This is evident in Table 8, where certain months have higher APE values, such as July 2025 at 13.71% and August 2025 at 17.96%.

The elevated prediction errors observed in July and August 2025 can be attributed to sudden upward movements in the actual HEXA stock price during those months. The actual prices in July and August 2025 were 5,375 and 5,625, respectively, representing sharp upward deviations from the broader downward trajectory that the ARIMA (0,2,1) model had extrapolated from the training data. ARIMA models parameterized on average trend and autocorrelation patterns in historical data are inherently designed to track smooth, gradual movements rather than abrupt price spikes that may be driven by external market events, sector-specific news flows, or sudden shifts in investor sentiment toward the heavy equipment sector. When actual prices surge rapidly over one or two months, the model's predictions remain anchored to the preceding trend, resulting in larger-than-average absolute errors for those specific periods.

This behavior reflects a known structural limitation of univariate linear time series models such as ARIMA: their responsiveness to sudden price fluctuations is limited because they do not incorporate exogenous information that might explain or anticipate such movements. Consequently, the MAPE of 5.26% accurately represents the model's average accuracy over the full comparison period, while the higher APEs in July and August 2025 signal periods in which the model was less responsive to abrupt market-driven price changes. Based on this description, the interpretation of model accuracy needs to consider both the average MAPE value and the error variation in each comparison period.

Comparison of Actual Data from May 2025 to April 2026 with Predicted Results

Table 8. Comparison of Actual Data and HEXA Stock Price Predictions

Month	Year	Actual	Prediction	Error	Abs Error	APE (%)
May	2025	5.050	4.686	364	364	7,21
June	2025	4.950	4.662	288	288	5,82
July	2025	5.375	4.638	737	737	13,71

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August	2025	5.625	4.615	1.010	1.010	17,96
September	2025	4.770	4.591	179	179	3,75
October	2025	4.650	4.567	83	83	1,78
November	2025	4.570	4.543	27	27	0,59
December	2025	4.300	4.519	-219	219	5,09
January	2026	4.330	4.495	-165	165	3,81
February	2026	4.520	4.472	48	48	1,06
March	2026	4.360	4.448	-88	88	2,02
April	2026	4.440	4.424	16	16	0,36

Source: RStudio output, processed by researchers

Table 8 shows that the model's predictions tend to fall gradually, while the actual comparison data fluctuates. The largest absolute error occurred in August 2025, at 1,010 with an APE of 17.96%. Furthermore, the APE in July 2025 also reached 13.71%. This finding suggests that while the model's average MAPE of 5.26% is considered excellent, there are still some months with error percentages exceeding 8%. Therefore, the MAPE value should not be interpreted as evidence that all monthly errors are consistently below 8%, but rather as an indicator of the average prediction error over the comparison period. This suggests that the model is able to follow the general level of data for some periods, but is less responsive to sharp spikes in actual prices.

HEXA Stock Price Forecast Results May 2026 to December 2027

Table 9. HEXA Stock Price Forecast for the Period May 2026 to December 2027

Month	Year	**Forecast**	**Lower 80**	**Upper 80**	**Lower 95**	**Upper 95**
May	2026	4.400	1.797	7.003	419	8.381
June	2026	4.376	1.620	7.133	160	8.592
July	2026	4.352	1.442	7.263	-99	8.804
August	2026	4.328	1.263	7.394	-360	9.017
September	2026	4.305	1.083	7.526	-622	9.231
October	2026	4.281	903	7.659	-885	9.447
November	2026	4.257	721	7.793	-1.151	9.664
December	2026	4.233	538	7.928	-1.417	9.883
January	2027	4.209	355	8.064	-1.686	10.104
February	2027	4.185	169	8.201	-1.956	10.327
March	2027	4.162	-17	8.340	-2.229	10.552
April	2027	4.138	-205	8.480	-2.503	10.779
May	2027	4.114	-394	8.621	-2.780	11.007
June	2027	4.090	-584	8.764	-3.058	11.238
July	2027	4.066	-776	8.908	-3.339	11.471
August	2027	4.042	-969	9.053	-3.621	11.706
September	2027	4.018	-1.163	9.200	-3.906	11.943
October	2027	3.995	-1.359	9.348	-4.193	12.182
November	2027	3.971	-1.556	9.498	-4.482	12.423
December	2027	3.947	-1.755	9.648	-4.773	12.667

Source: RStudio Output, Processed by Researchers.

Table 9 shows that the main forecast results gradually decreased from 4,400 in May 2026 to 3,947 in December 2027. The prediction interval boundaries widened as the forecast horizon expanded. Several lower bound values at the 80% and 95% intervals became negative at certain times. In the context of stock prices, these negative values do not necessarily imply a true negative stock price forecast, but rather indicate that the ARIMA model generates very wide uncertainty over long time horizons.

A negative value at the lower bound of the prediction interval should not be interpreted as a prediction that the HEXA stock price will actually be negative. In time series forecasting models, the prediction interval is a statistical range that reflects estimation uncertainty. A negative lower bound can occur due to the characteristics of the ARIMA model, the large residual variation, and the increasingly wide confidence interval at longer prediction horizons. Based on this explanation, for variables such as stock prices, where negative values are logically impossible, a negative lower bound of the prediction interval is more appropriately interpreted as an indication of very high prediction uncertainty, rather than a possible actual stock price value.

Methodologically, the main forecast results should be distinguished between the point prediction value and the prediction interval. The point prediction value represents the model's main estimate for each period, while the prediction interval represents the range of possibilities based on the model's statistical assumptions. If the lower bound of the prediction interval is below zero on data that is unlikely to be negative, the substantive interpretation may be directed towards a value approaching zero or as a signal of increasing model uncertainty. Therefore, forecast results should be used with caution, especially over long-term horizons, and should not be interpreted as certainty of actual future values.

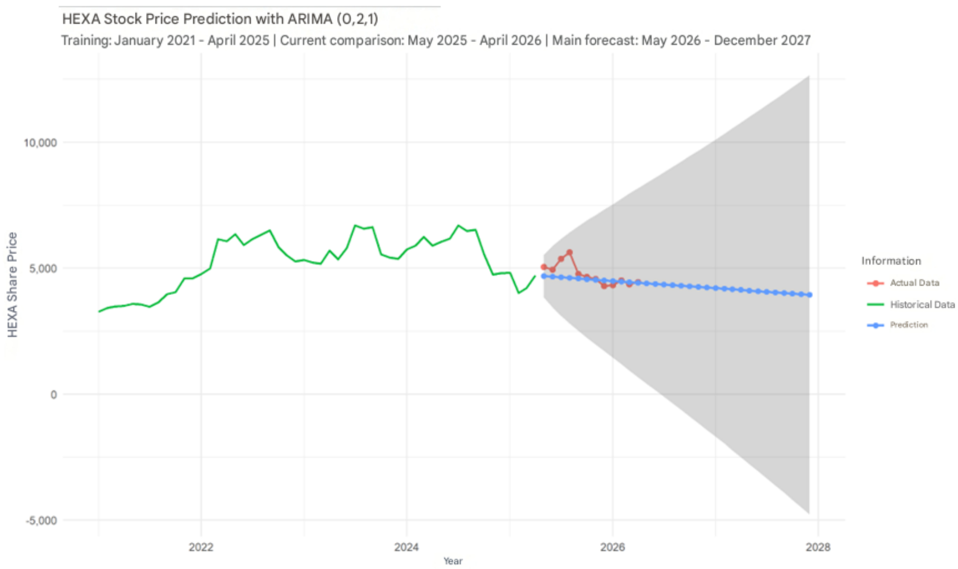

Figure 6. HEXA Stock Price Prediction Graph with ARIMA (0,2,1)
Source: RStudio Output, Processed by Researchers.

Figure 6 shows three main sections: historical data, actual comparison data, and prediction results. The prediction line shows a relatively smooth downward trend, while the gray area indicates the prediction interval. The widening interval area indicates that forecast uncertainty increases over longer prediction periods. Based on this description, the forecast results for May 2026 to December 2027 should be viewed as estimates based on historical patterns, not as a certainty of stock prices.

Based on these evaluation and forecast results, interpretation of the accuracy values and prediction intervals requires caution. The MAPE of 5.26% indicates that the average prediction error rate is low during the comparison period, but it does not necessarily mean that each month has an error below 8%. Furthermore, the negative value at the lower bound of the prediction interval represents a statistical lower bound, not a prediction of the actual negative stock price value. Because stock prices are logically impossible to be negative, a negative lower bound can be understood as an indication of a value approaching zero or as a signal that prediction uncertainty increases over a longer forecast horizon.

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CONCLUSION

Based on the attached RStudio output, the HEXA stock price data is non-stationary at the ADF level, as the ADF test yields a p-value of 0.7485. After second-order differencing, the ADF p-value becomes 0.0100, thus declaring the data stationary. Based on this description, the ARIMA model considered uses differencing order d = 2. The best model, based on the AIC and BIC comparison, is ARIMA (0,2,1), with an AIC of 753.2217 and a BIC of 757.0457. The parameter ma1 is significant with an estimate of -0.9502 and a p-value of 2.91E-46. Diagnostic checking indicates that the residuals are white noise based on the Ljung-Box test, with a p-value of 0.2731. However, the Q-Q plot shows deviations in the tails of the residual distribution, so the assumption of residual normality cannot be asserted based solely on the graph. The model's accuracy for the comparison period of May 2025 to April 2026 yielded a MAPE of 5.26%, an MAE of 268.67, and an RMSE of 398.31. The MAPE value indicates that the average absolute percentage error of the model was at a low level during the comparison period. However, this value does not necessarily mean that all monthly errors were consistently below 8%, as certain months, such as July 2025 and August 2025, experienced higher APEs. The output categorizes the MAPE as excellent, but the relatively higher RMSE compared to the MAE indicates some significant prediction errors. The main prediction result shows a gradual decline in the HEXA stock price from 4,400 in May 2026 to 3,947 in December 2027.

SUGGESTION

Future research is recommended to compare ARIMA with other methods such as SARIMA, ARIMAX, GARCH, or machine learning methods to evaluate the model's ability to capture stock price volatility more broadly. Additionally, researchers can add external variables such as transaction volume, the Jakarta Composite Index, the rupiah exchange rate, inflation, interest rates, commodity prices, and company fundamental indicators. Formal normality testing should also be added to further comprehensive residual diagnostic checking. For users of prediction results, ARIMA forecasts should not be used as the sole basis for investment decisions. Prediction results should be combined with fundamental analysis, technical analysis, heavy equipment industry conditions, and the latest market information. The widening prediction interval indicates significant uncertainty in the 2026-2027 period, requiring conservative interpretation. Furthermore, a negative lower bound of the prediction interval should not be interpreted as a negative stock price prediction, but rather as a statistical limit reflecting increasing model uncertainty over a longer forecast horizon. For stock price variables that are logically impossible to have negative values, a negative lower bound can be understood as an indication of a value approaching zero or as a signal that the prediction uncertainty range has become very wide.

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