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Prediction of Bank Central Asia stock prices after dividend distribution using ARIMA method

Sarif Surorejo[1], Muhammad Sulthon[2], Sawaviyya Anandianskha[3], Gunawan Gunawan[4]
[1,3]Information System, STMIK YMI TEGAL, Indonesia
[2,4]Informatics Engineering, STMIK YMI TEGAL, Indonesia

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ABSTRACT

This study explores the prediction of Bank Central Asia (BBCA) stock prices following the annual dividend distribution using the Autoregressive Integrated Moving Average (ARIMA) method. The primary goal is to provide a robust forecasting tool to aid investors and financial analysts in making informed decisions. The research employs a quantitative approach with a quasi-experimental design, analyzing weekly BBCA stock price data from January 2019 to February 2024. The findings demonstrate that the ARIMA (2, 1, 2) model provides stable and reliable predictions of BBCA stock prices, showing slight weekly variations but overall stability. Practically, these predictive models can be integrated into a web-based platform, allowing real-time stock price forecasting and broader accessibility for users. This study contributes to the financial literature by validating the ARIMA model's applicability in the Indonesian stock market and suggesting the exploration of hybrid models and external economic factors for future research.

Corresponding Author:

Muhammad Sulthon,
Informatics Engineering,
STMIK YMI TEGAL,
#1 Pendidikan Street, Tegal City, Central Java 52142, Indonesia.
Email: minyakgur13@gmail.com

1. INTRODUCTION

The capital market is a crucial pillar of a country's economy (Uddin et al., 2021), where the stock index is an important indicator reflecting the country's economic conditions (Baloch et al., 2020). Particularly, the Indonesian stock market has unique characteristics that distinguish it from other markets. Factors such as market volatility, investor behavior, and regulatory environment contribute to its complexity (Sudipa et al., 2023). BBCA stock, as one of the stocks with a large market capitalization in the Indonesian stock index, is significantly influenced by these unique market dynamics.

BBCA stock is one of the stocks with a large market capitalization in the Indonesian stock indeks (Sudipa et al., 2023), making it one of the main indicators in understanding stock market dynamics in Indonesia. After the annual dividend distribution, BBCA stock price fluctuations often cause uncertainty that can impact investor decisions (G. Liu & Zhang, 2020). The problem arises when investors and other stakeholders find it difficult to predict stock price movements, ultimately affecting their investment strategies and financial decisions (Gurdgiev & O'Loughlin, 2020). Previous research has not specifically addressed the prediction of stock prices following the annual dividend distribution. This research fills that gap by focusing on the prediction of Bank Central Asia (BBCA) stock prices after the dividend payout using the ARIMA method.

This research is important as it can help investors make more informed and data-driven decisions (Mandinach & Schildkamp, 2021), and enhance the understanding of stock market dynamics (Z. Liu et al., 2020). Given the complexity of the Indonesian stock market, the application of the ARIMA method needs to account for these local factors. The effectiveness of the ARIMA method in predicting stock prices in Indonesia may be influenced by unique patterns in market data, such as higher frequency of trading anomalies and external economic shocks that are more pronounced in emerging markets like Indonesia.

This study aims to address the problem of stock price prediction using the ARIMA method (Tang et al., 2020). The ARIMA method is a quantitative approach that has proven effective in analyzing and predicting time series data, but its application in the Indonesian market requires careful adaptation to local conditions. This research aims to identify specific patterns in historical stock price data that can assist in forecasting future price movements (Katoch & Sidhu, 2021) (Nabipour et al., 2020). Additionally, this study contributes to the financial literature, particularly in applying the ARIMA method for stock price prediction.

Researchers adapt the ARIMA model for specific Indonesian stock market data, considering unique local variables and conditions. Although there is optimism for potential improvements that can be achieved, this research explicitly acknowledges existing limitations and challenges (Oyewole et al., 2024). Researchers hope to provide nuanced insights into Indonesian stock price dynamics, especially BBCA stock, which can add value for investors, financial analysts, and other stakeholders in making more informed decisions and reducing financial risk (Shakil, 2021).

This research makes a significant contribution to the financial literature by offering empirical validation of the applicability of the ARIMA method in the Indonesian stock market, a relatively underexplored market in the literature. Additionally, by acknowledging the method's limitations, this research expands the understanding of how local factors and specific market conditions affect the effectiveness of predictive models. This helps to align expectations and potential outcomes that can be achieved through this approach. Furthermore, the results of this research are expected to be not only a theoretical reference but also a practical guide that can enrich strategies and financial decisions, minimize risk, and enhance investment returns in the Indonesian financial market.

The study by (Tarmanini et al., 2023) compares ARIMA and ANN for forecasting electricity demand using data from 709 Irish households, finding ANN more accurate for non-linear load data. Studies developed by (Khan & Alghulaiakh, 2020) compared the accuracy of auto ARIMA and two adjusted ARIMA models, finding that ARIMA (1133) was most accurate in forecasting Netflix stock prices over the past five years. (Chehelgerdi-Samani & Safi-Esfahani, 2021) studied cloud computing virtualization, highlighting resource optimization and energy reduction, but noted neglected migration minimization and future demands, with results showing the PCVM.ARIMA framework improved energy efficiency and QoS. The study (Yang et al., 2021) proposes an SA-optimized ARIMA-BPNN method for network traffic forecasting, highlighting the integration of linear and non-linear models to enhance prediction accuracy, with results showing improved performance over traditional models using MAE, RMSE, and MAPE evaluation metrics. Lastly, (Sirisha et al., 2022) used the LSTM method with an accuracy of 97.01%, proving superior to ARIMA and SARIMA in forecasting five-year profits. By adjusting this approach for the Indonesian stock market, this research aims to confirm and expand the findings of these studies in a local setting, contributing to a richer understanding of effective stock price prediction. Other methods such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Long Short-Term Memory (LSTM) networks have been used in Indonesia for stock price prediction, showing varying levels of success and emphasizing the need for careful method selection based on specific market conditions.

2. RESEARCH METHOD

Research Design

This study employs an analytical approach using BBCA stock price data sourced from Yahoo Finance. The objective is to predict BBCA stock prices following the annual dividend distribution using the ARIMA method. The research adopts a quantitative approach with a quasi-experimental design (Gopalan et al., 2020), selected to facilitate observation of the ARIMA prediction model's impact on BBCA stock price data under conditions that are not entirely controlled, simulating real financial market applications. Given the limitations of control groups and randomization, this design mirrors practical constraints and resource limitations in the field. Through this approach, it is hoped to better understand the model's performance in facing variations in stock market data complexity, providing valuable insights for understanding actual stock market dynamics.

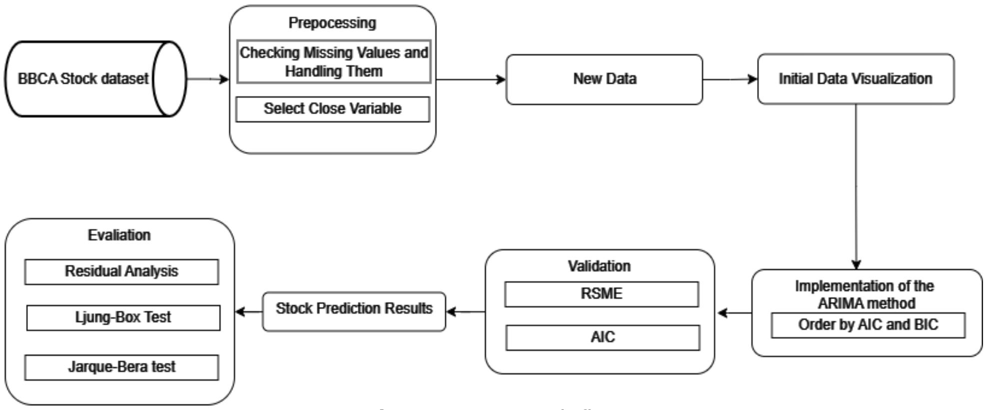

Figure 1. Research flow

Figure 1. depicts the stages of BBCA stock price prediction analysis using the ARIMA method. The process begins with the collection of BBCA stock data, followed by a preprocessing stage that includes handling missing values and differencing to achieve stationarity and generate new data. After the initial visualization of the new data, the ARIMA method is applied to determine the optimal parameters based on AIC and BIC. The constructed model is then validated using RMSE and AIC, and the prediction results are evaluated through residual analysis using the Ljung-Box and Jarque-Bera tests to ensure no significant autocorrelation and normal distribution of residuals. This systematic process aims to produce reliable and accurate BBCA stock price predictions.

Data Collection

In the Data Collection stage, the data used in this study is weekly BBCA stock price data obtained from Yahoo Finance, totaling 270 data points from the period January 1, 2019, to February 29, 2024. This data includes opening prices to trading volumes. This step aims to ensure the quality of data used in the analysis (Deepa et al., 2022). With a careful approach to data collection, it is hoped that the analysis results can provide valuable contributions to understanding BBCA stock price movements.

Preprocessing

In the preprocessing stage of data for the ARIMA model used in stock price prediction, the first crucial step is examining and cleaning the data (Deng et al., 2020). This includes identifying and handling missing values as well as removing outliers that could disrupt the analysis. Ensuring that the data is free from these issues is vital because missing values and outliers can cause distortions in prediction results, reducing model accuracy (Sun et al., 2023). After cleaning the data, the next step is converting the data into a time series format with dates set as indices and frequency set to weekly. This step is important as the ARIMA model requires chronologically ordered data to produce accurate and reliable predictions. Thus, examining the data at the beginning of the prediction process is a foundational step ensuring data integrity and quality, ultimately enhancing model prediction accuracy.

Implementation of the ARIMA Method

Implementing the ARIMA method in stock prediction begins with collecting historical stock price data and ensuring the data is complete and chronologically ordered. The next stage is testing data stationarity using the Augmented Dickey-Fuller (ADF) test and applying differencing if necessary to achieve stationarity. After the data becomes stationary, optimal parameter selection for the ARIMA model is performed using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The optimal autoregressive (p), differencing (d), and moving average (q) parameters are then used to build the ARIMA model (Schaffer et al., 2021).

The general form of the ARIMA model is represented by the following equations:

$$y_t = c + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots + \emptyset_p y_{t-p} + \epsilon_t \quad (1)$$

$$y'_t = (1 - B)^d \, y_t \quad (2)$$

$$y_t = \mu + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_p \epsilon_{t-p} \quad (3)$$

$$y_t = c + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots + \emptyset_p y_{t-p} + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_p \epsilon_{t-p} \quad (4)$$

In the ARIMA model, yt represents the value at time t. The constant used in the model is denoted by c. The autoregressive coefficients, which describe the influence of previous values on the current value, are indicated by $\phi 1$, $\phi 2$, …, ϕp. The random error at time t is represented by ϵt. The backshift operator, which is used to shift the time value backward, is denoted by B. The order of differencing, required to achieve stationarity, is indicated by d. The moving average coefficients, which describe the influence of previous random errors on the current value, are denoted by $\theta 1$, $\theta 2$, … , θq . All these components work together to form the ARIMA model used for stock price prediction.

Validate Model

After building the ARIMA model, the next important step is validating the model to ensure its accuracy in predicting stock prices. Two main metrics used in this model validation are Root Mean Square Error (RMSE) and Akaike Information Criterion (AIC) (Hodson, 2022), (Portet, 2020).

The RMSE assesses the accuracy of the model's predictions by comparing them to the actual values. It quantifies the prediction error in the same units as the original data. A lower RMSE value signifies better model performance in forecasting the data. AIC is a metric used to select the best model among different models by considering the model's fit to the data and its complexity (the number of parameters used). A model with a lower AIC value is considered better as it indicates a balance between data fit and model complexity.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(yi - \hat{y}i)^2} \quad (5)$$

Where n is the number of data points, yi is the actual value, and $\hat{y}i$ is the predicted value.

$$AIC = 2k - 2\ln(L) \quad (6)$$

Where k is the number of parameters in the model, and L is the likelihood value of the model.

Evaluate Prediction Results

After building the ARIMA model, the next important step is evaluating the model to ensure its accuracy in predicting stock prices. Evaluation is done through residual analysis using the Ljung-Box test to check for autocorrelation in the residuals and the Jarque-Bera test to ensure that the residuals are normally distributed (Abbasi et al., 2021; Hassani & Yeganegi, 2020; Y. Liu & Liu, 2022). This evaluation process aims to ensure that the ARIMA model used provides reliable and accurate prediction results.

Residual plots are used to visually examine residuals to detect any clear patterns. In this method, residuals are plotted against time or predicted values. Ideally, residuals should be randomly scattered around zero. Such a pattern indicates that the model has successfully captured all systematic patterns in the data. If residuals do not show random scatter, it may indicate that the model has missed some underlying structures in the data. The Ljung-Box test is used to check for autocorrelation in the model's residuals to ensure that the residuals do not show specific patterns and can be considered random noise. Results indicating no significant autocorrelation mean that the model has successfully captured patterns in the data. The Jarque-Bera test is used to check the normality of the residual distribution. This is done to ensure that the residuals are normally distributed, which is an important assumption in the ARIMA model. The test results indicate whether the skewness and kurtosis of the residuals approach an ideal normal distribution.

$$e_t = y_t - \hat{y}_t \quad (7)$$

Where e_t is the residual at time t, y_t is the actual value, and $\hat{y}_t$ is the value predicted by the model.

$$Q = n\,(n+2)\sum_{k=1}^{m}\frac{\hat{p}_k^2}{n-k} \quad (8)$$

Where Q is the test statistic, n is the number of observations, m is the maximum lag, and $\hat{p}_k^2$ is the autocorrelation at lag k.

$$JB = \frac{n}{6}\,(S^2 + \frac{(K-3)^2}{4}) \quad (9)$$

Where JB is the test statistic, n is the number of observations, S is the skewness, and K is the kurtosis.

3. RESULTS AND DISCUSSIONS

This chapter outlines the results of the analysis using the Autoregressive Integrated Moving Average (ARIMA) method to predict the stock price of PT Bank Central Asia Tbk (BBCA) before the annual dividend distribution. The researchers present the process and results of stationarity tests, optimal ARIMA model selection, and the evaluation of the model's effectiveness in projecting stock price movements. The analysis is complemented with data visualizations to demonstrate the model's prediction accuracy against actual data and the evaluation of its performance using relevant statistical metrics.

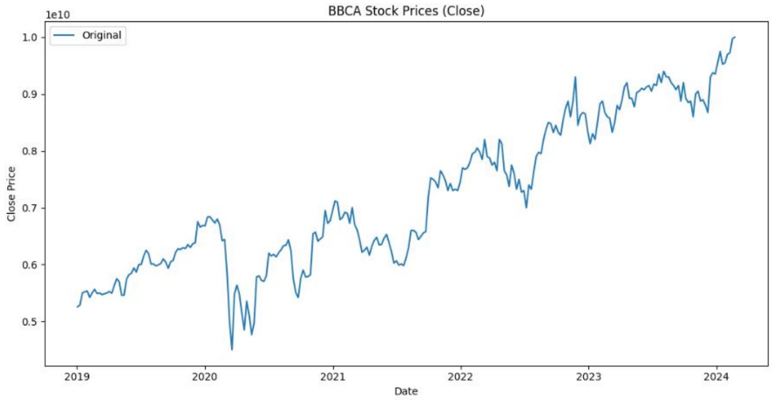

Figure 2. Bank central asia share price plot

Figure 2. shows the closing price plot of BBCA stock for the period from 2019 to 2024. The graph indicates an overall upward trend in stock prices with some significant fluctuations. This plot illustrates the development of BBCA stock prices, which tend to increase over the period despite some market fluctuations.

Data Preprocessing and Stationarity Test

In the data preprocessing stage for PT Bank Central Asia Tbk (BBCA) stock prices, missing values were examined to ensure dataset integrity. Initial examination results showed no missing values in all columns, including 'Date', 'Open', 'High', 'Low', 'Close', 'Adj Close', and 'Volume'. The variable chosen for further analysis was the 'Close' variable. After ensuring no missing values, the data was filtered based on the desired period and set to weekly frequency. The 'Close' variable was then used as new data for analysis with the ARIMA method. This process ensures that the dataset is ready for further analysis, guaranteeing the accuracy and reliability of prediction results.

In the stationarity test stage, researchers applied the Augmented Dickey-Fuller (ADF) test to assess whether the BBCA stock price time series contained a unit root indicating non-stationarity. The test results showed that the initial data had an ADF Statistic of -0.558253 and a p-value of 0.880139, which is greater than 0.05, thus requiring differencing to convert the series to stationary. After transformation, the ADF Statistic changed to -11.327465 with a p-value of 0.000000, which is less than 0.05, indicating that the data has become stationary. These test and transformation results affirm the effectiveness of the process in achieving stationarity before proceeding to ARIMA modeling.

Model Selection and Validation

In the selection of the ARIMA model for BBCA stock price prediction, the researchers conducted a series of analyses to determine the best combination of autoregressive (p), differencing (d), and moving average (q) parameters. This process involved automatic searching to minimize Root Mean Square Error (RMSE) and Akaike Information Criterion (AIC) to find a model that can balance data fit with model complexity efficiently. During the model validation process, several evaluation metrics were used to assess model performance, including Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). The chosen ARIMA (2 1 2) model had an RMSE of 13,038,401.352643441 and an MAE of 8,614,981.103464987, indicating efficiency in explaining data variation with minimal parameters.

Table 1. Predict the result of ARIMA

Date	Forecasted Price (IDR)
2024-03-07	9.989479e+09
2024-03-14	9.995336e+09
2024-03-21	1.000096e+10
⋮	⋮
2024-09-12	9.997172e+09
2024-09-19	9.996396e+09
2024-09-26	9.994617e+09

Table 1. shows the predicted BBCA stock prices for the period from March 7, 2024, to September 26, 2024, based on the ARIMA (2 1 2) model. The stock prices are predicted to fluctuate but remain overall stable, ranging from 9.989 billion IDR to 10.00096 billion IDR. This prediction indicates that BBCA stock prices will experience slight weekly variations but stay within a relatively stable range throughout the period, providing a reliable picture for analysis and investment decisions.

Prediction Results

After determining the best model, ARIMA (2 1 2), the researchers predicted BBCA stock prices for the period from March 2024 to September 2024. The prediction results show variations in BBCA stock prices during this period. Here are some key prediction points: on March 7, 2024, the stock price is predicted to be 9.989479e+09 IDR, then slightly increase to 9.995336e+09 IDR on March 14, 2024, and continue to show fluctuations with the highest prediction of 1.000096e+10 IDR on March 21, 2024. This trend continues with stock prices predicted to range between 9.992656e+09 IDR to 9.996396e+09 IDR, finally reaching 9.994617e+09 IDR on September 26, 2024.

Diagnostic analysis was performed to confirm that the model's residuals are normally distributed and free from significant autocorrelation. The primary tests applied were the Ljung-Box test and the Jarque-Bera test. The Ljung-Box test evaluates autocorrelation in the model's residuals, and the findings show no significant autocorrelation. The Jarque-Bera test assesses the normality of the residuals' distribution, indicating that they are normally distributed. Consequently, the ARIMA (2 1 2) model demonstrates good performance, with residuals meeting the necessary assumptions, thereby ensuring that the model's predictions are reliable and valuable for analysis and investment decision-making.

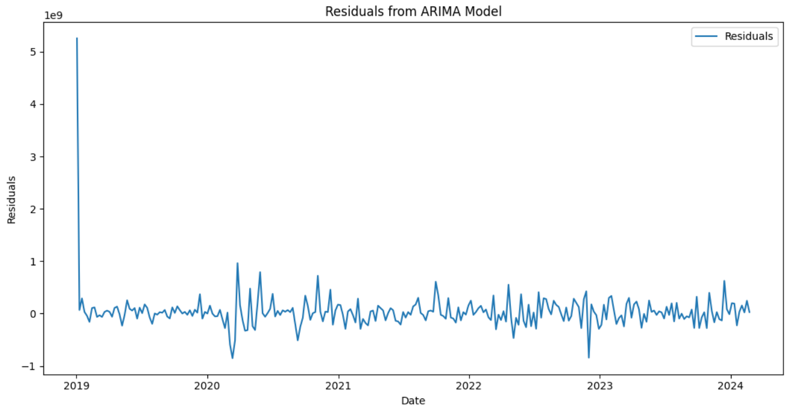

Figure 3. Residual plot of an ARIMA model

Figure 3. shows the residuals of the ARIMA model scattered randomly around zero without clear patterns, indicating a model that fits the data well. There are some peaks at the beginning of the data indicating greater variation at those points.

Comparison with Previous Research

This study's findings align with previous research that utilized ARIMA models for stock price prediction but also highlight unique insights specific to the Indonesian stock market. For instance, previous research demonstrated that while ARIMA models can be effective, Artificial Neural Networks (ANN) often outperform ARIMA in non-linear data scenarios. Similarly, other researchers found that the ARIMA (1133) model was most accurate in forecasting Netflix stock prices, which emphasizes the importance of model tuning for specific datasets. Other researchers highlighted the effectiveness of combining ARIMA with other methodologies for improved performance, such as the PCVM.ARIMA framework. Additional studies also showed the benefits of integrating linear and non-linear models, like the SA-optimized ARIMA-BPNN method, which enhanced prediction accuracy for network traffic.

In comparison, this study provides empirical validation of the ARIMA model's applicability in a relatively underexplored market, the Indonesian stock market. It emphasizes the need for careful adaptation of predictive models to local conditions, addressing unique patterns and external economic shocks more pronounced in emerging markets. This research not only corroborates the effectiveness of ARIMA but also contributes additional insights into how local factors can impact predictive accuracy, thereby enriching the existing financial literature.

4. CONCLUSION

In conclusion, this study effectively utilized the ARIMA (2, 1, 2) model to predict BBCA stock prices following the annual dividend distribution, demonstrating stable and reliable predictions. The results of this research will be applied practically by providing investors and financial analysts with a robust tool for forecasting stock prices, enhancing their decision-making processes. Additionally, the implementation of these predictive models can be integrated into a web-based platform, allowing real-time stock price forecasting and broader accessibility for users. The implications for financial decision-making include improved investment strategies, better timing of market entry and exit, and enhanced risk management. Future research should explore hybrid models and incorporate external economic factors to further enhance prediction accuracy and model robustness.

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