Journal of Actuarial, Finance and Risk Management (JAFRM)
Vol. 3(2), December, 2024.
http://e-journal.president.ac.id/presunivojs/index.php/JAFRM/index

Forecasting Weekly Stock Price of PT. Aneka Tambang Tbk (ANTM) Using ARIMA Box-Jenkins Method

Andreanne Intan Sulistyo Wardhani[1, *], Mokhammad Ridwan Yudhanegara[2]

[1] *Study Program of Actuarial Science, School of Business, President University, Bekasi, 17550, Indonesia*

[2] *Mathematics Education Department, Universitas Singaperbangsa, Karawang, 41361, Indonesia*

[*]*Corresponding author: andreanne.wardhani@student.president.ac.id*

Receive: October, 24 2024, Revised: January 12, 2025, Accepted: January 13, 2025

Abstract— The dynamic movement of stock prices in the economic world demands the ability to predict future trends, especially for investors and companies making strategic decisions. This study focuses on forecasting the weekly stock price of PT Aneka Tambang Tbk (ANTM) using the Autoregressive Integrated Moving Average (ARIMA) method based on the Box-Jenkins approach. The data analyzed consist of weekly closing prices from January 1, 2022, to January 27, 2024, totaling 109 observations. The calculation shows that the ARIMA (3,1,0) model is the most suitable for this dataset, achieving a relatively very accurate prediction, as indicated by a Mean Absolute Percentage Error (MAPE) of 7.68%. This result offers valuable insights to help investors and companies anticipate stock price changes, supporting more informed and strategic investment planning.

Keywords— ARIMA; Forecasting; Stock Price

I. INTRODUCTION

In today's rapidly changing economic landscape, stock price movements are a critical phenomenon that investors and companies must monitor. Stock prices, defined as the cost per share traded in the capital market [1], are not only indicators of market dynamics but also essential tools for shaping investment strategies, managing risks, and planning finances. The ability to predict stock price movements accurately provides significant advantages, enabling stakeholders to make better decisions while minimizing risks. To this end, various statistical and computational forecasting methods have been developed, including time series analysis techniques.

Among time series analysis methods, the ARIMA (Autoregressive Integrated Moving Average) model stands out as a versatile and effective tool for time series forecasting. First introduced by George Box and Gwilym Jenkins in 1976, ARIMA is widely recognized under the notation ARIMA (p,d,q) [2]. This method is particularly suitable for data exhibiting patterns like trends and seasonality, as it combines simplicity, interpretability, and reliability. Compared to GARCH models that primarily focus on volatility or machine learning techniques like neural networks, which require high computational resources, ARIMA offers a straightforward yet robust approach. Its reliance on historical data makes it an ideal choice for financial time series forecasting, especially when data is limited, or interpretability is prioritized.

This study applies the ARIMA method to forecast the weekly stock price of PT Aneka Tambang Tbk (ANTM) for a four-week period from January 6, 2024, to January 27, 2024. The analysis uses weekly closing stock price data from January 1, 2022, to January 27, 2024, totaling 109 observations. Established in 1968, PT Aneka Tambang Tbk is a state-owned mining company specializing in nickel, gold, and bauxite commodities [3]. The goal of this forecasting is to provide investors with actionable insights into future trends, serving as a practical reference for investment strategies.

While previous studies have extensively applied ARIMA for stock price forecasting, certain gaps remain. Triputra et al. (2022) predicted PT Aneka Tambang Tbk's stock prices for December 2021 using historical data from July to November 2021, identifying ARIMA (3,2,0) as the best model [4]. Alim (2023) extended this exploration by comparing ARIMA with neural network-based models like LSTM and CNN-LSTM for forecasting ANTM and ICBP stock prices [5]. Additional studies by Manurung and Nugraha (2023), Olivia and Nugraha (2023), and Singgih and Nugraha (2023) demonstrated ARIMA's effectiveness for forecasting stock prices in various contexts, including PT OCBC NISP Tbk, PT Bank Central Asia Tbk, and Taiwan Semiconductor Manufacturing Company Limited [6] [7] [8]. This study addresses gaps by using updated data until January 2024 and focusing on forecasting the weekly stock prices of PT Aneka Tambang Tbk (ANTM). Unlike previous studies comparing ARIMA with modern methods like LSTM, this research highlights ARIMA's reliability as a simple, practical approach and can work for datasets with short time spans.

II. Literature Review

A. Time Series Analysis

A time series is a set of data points collected in chronological order, such as daily, weekly, or monthly observations. Each data point depends on previous ones, influencing future values. Time series analysis aims to understand these dependencies, identify patterns or trends, and make forecasts based on historical data [9]. Techniques in time series analysis include identifying trends, recognizing seasonal patterns, forecasting, and analyzing temporal correlations. Forecasting enables decision-making by revealing insights from historical trends, with ARIMA (Autoregressive Integrated Moving Average) being a widely used method [10].

B. Stationarity and Differencing

In time series analysis using the ARIMA (Autoregressive Integrated Moving Average) method, the concepts of stationarity and differencing play an important role in ensuring the resulting model can provide accurate predictions. Stationarity refers to the statistical property of a time series having a constant mean [10]. Since ARIMA models work best with stationary data, this property must be ensured before applying the model. Using R Studio, stationarity can be tested with the Augmented Dickey-Fuller (ADF) Test, where a p-value below 0.05 confirms stationarity. If the time series is not initially stationary, a differencing step is used to achieve stationarity. Differencing process create a new time series that is more stationary than the original time series. In the ARIMA method, the differencing step can be applied one or more times until the resulting time series becomes stationary. The differencing process can be presented using the following formula as the fundamental to understanding how differencing stabilizes a time series for ARIMA modeling.

$$W_t = \Delta^d Y_t \tag{1}$$

First-order differencing: $$W_t = \Delta Y_t = Y_t - Y_{t-1} \tag{2}$$

Second-order differerncing: $$W_t = \Delta^2 Y_t = \Delta(\Delta Y_t) = Y_t - 2Y_{t-1} + Y_{t-2} \tag{3}$$

Third-order differencing: $$W_t = \Delta^3 Y_t = \Delta(\Delta^2 Y_t) = \Delta(Y_t - 2Y_{t-1} + Y_{t-2}) \tag{4}$$

C. Auto-Correlation Function (ACF) and Partial Auto-Correlation Function (PACF)

The Auto-Correlation Function (ACF) measures the relationship between current and past values in a time series. ACF is used to find the moving average (MA) order in the ARIMA model through the cutoff at lag k. The Partial Autocorrelation (PACF) determines the autoregressive (AR) order in the ARIMA model by isolating direct relationships after removing prior correlations. The autoregressive (AR) order and moving average (MA) order obtained through ACF and PACF are used in determining the ARIMA model [10].

D. Error Estimation

Error estimation is an important stage in evaluating the performance of ARIMA models in time series analysis. In forecasting using the ARIMA method, error estimation is performed to evaluate how well the model has estimated or modeled the actual behavior of the time series data. Some error estimation used to measure the error of ARIMA models include Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). MAE measures the average of the absolute difference between the observed value and the value predicted by the model. MAPE measures the average percentage of error between the observed value and the value predicted by the model. MSE measures the average of the squares of the difference between the observed and predicted values, while RMSE is the square root of MSE [11].

III. Methodology

A. Box-Jenkins Method

The ARIMA (Autoregressive Integrated Moving Average) model that originally develop by George Box and Gwilym Jenkins is one of the most commonly used approaches in forecasting time series, including stock prices [2]. The ARIMA model combines autoregressive (AR) and moving averaging (MA) elements to capture patterns and trends in time series data. In time series forecasting using ARIMA method, the model must satisfy the stationary assumption. To forecast nonstationary data, calculations can be done by transforming the nonstationary series into a stationary series by performing differencing.

1. *Autoregressive (AR)*

   The Autoregressive (AR) model show that current data (Yt) depends on data from the previous period (Yt-p). The equation of AR model can be written as:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + e_t \tag{5}$$

2. *Moving Average (MA)*

   The Moving Average (MA) model show that current data (Y_t) depends on the error in the present data (e_t) and past data (e_{t-q}). The equation of MA model can be written as:

$$Y_t = e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q} \tag{6}$$

3. *Autoregressive Integrated Moving Average (ARIMA)*

   Autoregressive (AR) model and Moving Average (MA) equation can be combined and written as the ARMA (p,q):

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q} \tag{7}$$

   Forecasting nonstationary data can be done with the ARIMA (p,d,q) method by combining the AR and MA methods and using differencing $W_t = \nabla^d Y_t$ [10]. ARIMA equation can be written as:

$$W_t = \phi_1 W_{t-1} + \phi_2 W_{t-2} + \cdots + \phi_p W_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q} \tag{8}$$

Y_t : Data at time *t*

Y_{t-p} : Data at *p* period before time *t*

e_t : Error at time *t*

e_{t-q} : Error at *p* period before time *t*

ϕ_p : AR coefficient at order *p*

θ_q : MA coefficient at order *q*

W_t : Differencing process

To perform forecasting using the ARIMA method, there are steps shown in Figure 1. The data used for forecasting using ARIMA method needs to be stationary checked through ADF Test. For nonstationary data, it is needed to be differencing until the result is stationary. Then the candidate model for the data that has been stationary can be determined through the ACF and PACF at lag k, and the parameters for each candidate model are determined. To determine the best model to use for forecasting, it is important to conduct a diagnostic test before forecasting. Diagnostic test conducted using the Shapiro test to determine whether the residuals follow a normal distribution and the Ljung Box test to determine whether the residuals are free from autocorrelation, both of which are indicated by a p-value > 0.05.

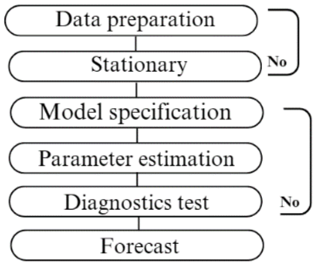

Figure. 1 ARIMA forecasting steps

IV. Result And Discussion

A. Data Preparation

The data used in this analysis is PT Aneka Tambang Tbk (ANTM.JK) weekly stock price data from January 01, 2022 to January 27, 2024 with a total of 109 data. 105 data as data training and 4 data as data test. Data shown in TABLE 1 and Figure 2 as graph. The data is taken from Yahoo Finance website and is processed using R Studio.

TABLE 1
Data of The Stock Price of PT Aneka Tambang Tbk

Date	Close	Date	Close	Date	Close	Date	Close
01/01/2022	2230	07/16/2022	1780	01/28/2023	2330	08/12/2023	1950
01/08/2022	1950	07/23/2022	1955	02/04/2023	2220	08/19/2023	1990
01/15/2022	1945	07/30/2022	2020	02/11/2023	2090	08/26/2023	1955
01/22/2022	1770	08/06/2022	2220	02/18/2023	2000	09/02/2023	1945
01/29/2022	1810	08/13/2022	2060	02/25/2023	1995	09/09/2023	1900
02/05/2022	1845	08/20/2022	1955	03/04/2023	1880	09/16/2023	1850
02/12/2022	2090	08/27/2022	1900	03/11/2023	1895	09/23/2023	1815
02/19/2022	2220	09/3/2022	1975	03/18/2023	1895	09/30/2023	1715
02/26/2022	2450	09/10/2022	2040	03/25/2023	2090	10/07/2023	1755
03/05/2022	2520	09/17/2022	2040	04/01/2023	2100	10/14/2023	1825
03/12/2022	2390	09/24/2022	1940	04/08/2023	2110	10/21/2023	1725
03/19/2022	2660	10/01/2022	1935	04/15/2023	2100	10/28/2023	1655
03/26/2022	2510	10/08/2022	1820	04/22/2023	2100	11/04/2023	1625
04/02/2022	2800	10/15/2022	1800	04/29/2023	2040	11/11/2023	1635
04/09/2022	2780	10/22/2022	1835	05/06/2023	2000	11/18/2023	1605
04/16/2022	2740	10/29/2022	1915	05/13/2023	1955	11/25/2023	1705
04/23/2022	2600	11/05/2022	2120	05/20/2023	1920	12/02/2023	1685
04/30/2022	2600	11/12/2022	1960	05/27/2023	1895	12/09/2023	1670
05/07/2022	2330	11/19/2022	1950	06/03/2023	1975	12/16/2023	1665
05/14/2022	2490	11/26/2022	2040	06/10/2023	2060	12/23/2023	1705
05/21/2022	2470	12/03/2022	1935	06/17/2023	2010	12/30/2023	1675
05/28/2022	2500	12/10/2022	2020	06/24/2023	1950	01/06/2024	1625
06/04/2022	2290	12/17/2022	2000	07/01/2023	1975	01/13/2024	1645
06/11/2022	2110	12/24/2022	1985	07/08/2023	2000	01/20/2024	1575

06/18/2022	1970	12/31/2022	1985	07/15/2023	1975	01/27/2024	1525
06/25/2022	1750	01/07/2023	2150	07/22/2023	1960		
07/02/2022	1715	01/14/2023	2320	07/29/2023	2020		
07/09/2022	1540	01/21/2023	2300	08/05/2023	1990		

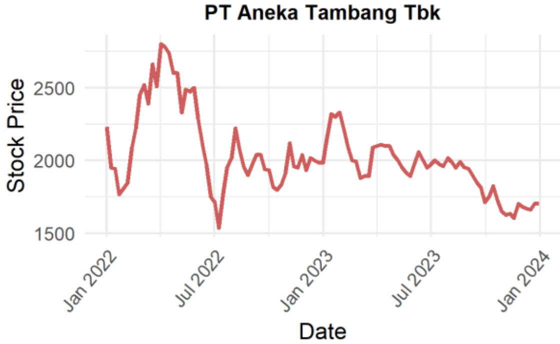

Figure. 2 Graph of PT Aneka Tambang Tbk Stock Price

B. Stationary Check

Before processing the data, the data must be confirmed to be stationary using the Augmented Dickey-Fuller Test method in R Studio. If the data has a p-value below 0.05, then the data can be considered stationary. In Figure 3, it is shown the plot of PT Aneka Tambang Tbk stock price with p-value obtained from the Augmented Dickey-Fuller Test is 0.0582. This value exceeds the significance level of 0.05, which indicates that the data is not stationary.

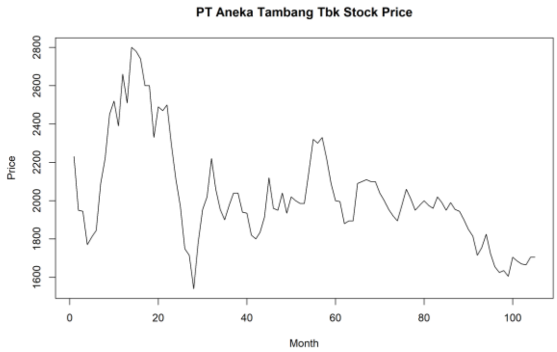

Figure. 3 Plot of PT Aneka Tambang Tbk Stock Price

To make the data stationary, differencing is required using the "diff(data)" code in R Studio. In Figure 4, it is shown the plot of first difference of PT Aneka Tambang Tbk Stock Price after performing first differencing with p-value obtained from the Augmented Dickey-Fuller Test is 0.01. The p-value after first differencing is less than 0.05 indicates that the data is stationary and order d used in ARIMA model is 1.

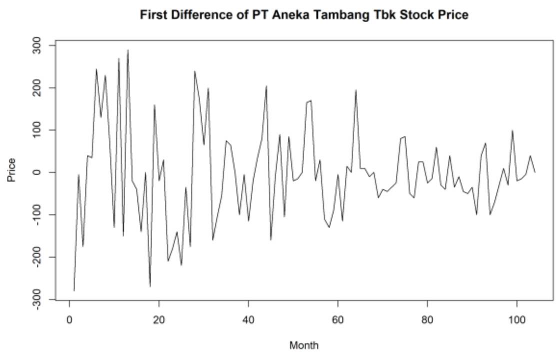

Figure. 4 Plot of First Difference PT Aneka Tambang Tbk Stock Price

C. Model Specification

The ARIMA model can be specified from the Auto-Correlation Function (ACF) and Partial Auto-Correlation Function (PACF) plot of the data. Figure 5 shows the ACF and PACF plot for PT Aneka Tambang Tbk after the first differencing.

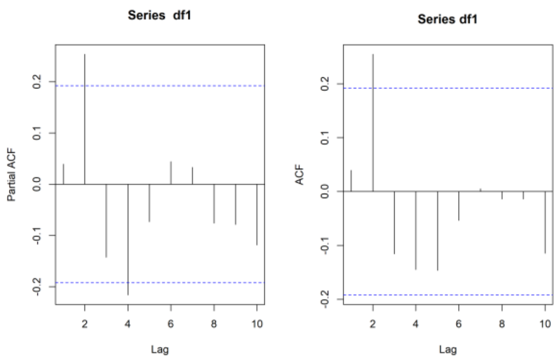

Figure. 5 Plot of ACF and PACF First Difference of PT Aneka Tambang Tbk Stock Price

Based on the information provided by Figure 5, it is known that PACF cuts off at a lag time of 4 and ACF cuts off at a lag time of 2. Thus, the order of p is determined as 4 and order of q is determined as 2. TABLE 2 shows the ARIMA model arranged based on these parameters.

TABLE 2
ARIMA Model Specification

No	ARIMA Model	p	d	q
1	ARIMA (0,1,0)	0	1	0
2	ARIMA (0,1,1)	0	1	1
3	ARIMA (0,1,2)	0	1	2
4	ARIMA (1,1,0)	1	1	0
5	ARIMA (1,1,1)	1	1	1
6	ARIMA (1,1,2)	1	1	2
7	ARIMA (2,1,0)	2	1	0
8	ARIMA (2,1,1)	2	1	1
9	ARIMA (2,1,2)	2	1	2
10	ARIMA (3,1,0)	3	1	0
11	ARIMA (3,1,1)	3	1	1
12	ARIMA (3,1,2)	3	1	2
13	ARIMA (4,1,0)	4	1	0
14	ARIMA (4,1,1)	4	1	1
15	ARIMA (4,1,2)	4	1	2

D. Parameter Estimation

The parameters of the Autoregressive (AR) formula are denoted as φ with order p. While the parameters of the Moving Average (MA) formula are denoted as θ with order q. TABLE 3 shows that by using the summary(model) code, the value of each parameter as well as Log Likelihood and Akaike Information Criterion (AIC) can be obtained.

TABLE 3
Parameter Estimation for ARIMA Model

Model ARIMA	AR1	AR2	AR3	AR4	MA1	MA2	Log Likelihood	AIC
(0,1,0)							-637.56	1277.11
(0,1,1)					0.0275		-637.5	1279
(0,1,2)					0.0470	0.3792	-631.72	1269.45
(1,1,0)	0.0425						-637.47	1278.94
(1,1,1)	0.4764				-0.3848		-637.03	1280.07
(1,1,2)	0.0262				0.0251	0.3823	-631.72	1271.44
(2,1,0)	0.0313	0.2659					-633.82	1273.64
(2,1,1)	-0.1714	0.2832			0.2178		-633.38	1274.77
(2,1,2)	0.2100	-0.6302			-0.1861	1	-629	1267.99
(3,1,0)	0.0665	0.2706	-0.1489				-632.71	1273.41
(3,1,1)	0.9265	0.2436	-0.3553		-0.9339		-629.67	1269.34
(3,1,2)	0.5159	-0.1654	-0.2532		-0.4894	-0.5022	-629.79	1271.59
(4,1,0)	0.0351	0.3231	-0.1333	-0.2172			-630.28	1270.55
(4,1,1)	0.2578	0.3090	-0.1928	-0.1870	-0.2343		-630.07	1272.14
(4,1,2)	1.2071	-0.5782	-0.4081	0.2338	-1.1959	0.8644	-630.41	1274.82

E. Residual Analysis

Determining the best ARIMA model is performed using the Shapiro Test and the Ljung-Box Test. Through these tests, the ARIMA model with a p-value that exceeds 0.05 will be selected. TABLE 4 shows the results of the Shapiro Test and Ljung-Box Test and the ARIMA models that satisfy the condition. Models that passed the residual test will be forecasted and the error of each model will be calculated.

TABLE 4
Result of Residual Analysis

No	Model ARIMA	Shapiro Test	Ljung-Box Test	AIC	Result
1	ARIMA (0,1,0)	0.01631	0.6939	1277.11	Not Passed
2	ARIMA (0,1,1)	0.01649	0.9721	1279	Not Passed
3	ARIMA (0,1,2)	0.4794	0.9886	1269.45	Passed
4	ARIMA (1,1,0)	0.01687	0.8729	1278.94	Not Passed
5	ARIMA (1,1,1)	0.02591	0.4689	1280.07	Not Passed
6	ARIMA (1,1,2)	0.467	0.9821	1271.44	Passed
7	ARIMA (2,1,0)	0.1903	0.7195	1273.64	Passed
8	ARIMA (2,1,1)	0.2595	0.9199	1274.77	Passed
9	ARIMA (2,1,2)	0.004635	0.9286	1267.99	Not Passed
10	ARIMA (3,1,0)	0.3198	0.7425	1273.41	Passed
11	ARIMA (3,1,1)	0.2186	0.8887	1269.34	Passed
12	ARIMA (3,1,2)	0.1786	0.9696	1271.59	Passed
13	ARIMA (4,1,0)	0.2018	0.8478	1270.55	Passed
14	ARIMA (4,1,1)	0.2132	0.9541	1272.14	Passed
15	ARIMA (4,1,2)	0,09543	0.9066	1274.82	Passed

F. Forecast

TABLE 5
Forecasting Value of The ARIMA (0,1,2)

Date	Actual Data	Predicted Data	Lower Bound	Upper Bound
2024-01-06	1625	1726,697	1554.0097	1899.384
2024-01-13	1645	1725,608	1475.5838	1975.632
2024-01-20	1575	1725,608	1374.6481	2076.568
2024-01-27	1525	1725,608	1296.8498	2154.366

TABLE 6
Forecasting Value of The ARIMA (1,1,2)

Date	Actual Data	Predicted Data	Lower Bound	Upper Bound
2024-01-06	1625	1726.987	1554.3147	1899.658
2024-01-13	1645	1726.585	1476.0475	1977.123
2024-01-20	1575	1726.575	1374.2116	2078.938
2024-01-27	1525	1726.574	1294.8166	2158.332

TABLE 7
Forecasting Value of The ARIMA (2,1,0)

Date	Actual Data	Predicted Data	Lower Bound	Upper Bound
2024-01-06	1625	1715.636	1539.2915	1891.981
2024-01-13	1645	1715.969	1462.6466	1969.292
2024-01-20	1575	1718.808	1377.3688	2060.247
2024-01-27	1525	1718.985	1306.2575	2131.713

TABLE 8
Forecasting Value of The ARIMA (2,1,1)

Date	Actual Data	Predicted Data	Lower Bound	Upper Bound
2024-01-06	1625	1716.148	1540.5652	1891.731
2024-01-13	1645	1714.237	1460.1013	1968.373
2024-01-20	1575	1717.722	1373.5804	2061.863
2024-01-27	1525	1716.583	1304.8271	2128.34

TABLE 9
Forecasting Value of The ARIMA (3,1,0)

Date	Actual Data	Predicted Data	Lower Bound	Upper Bound
2024-01-06	1625	1716.569	1542.164	1890.975
2024-01-13	1645	1711.383	1456.404	1966.361
2024-01-20	1575	1714.169	1368.111	2060.227

2024-01-27	1525	1711.228	1304.174	2118.281

TABLE 10
Forecasting Value of The ARIMA (3,1,1)

Date	Actual Data	Predicted Data	Lower Bound	Upper Bound
2024-01-06	1625	1735.216	1566.33	1904.103
2024-01-13	1645	1748.999	1511.04	1986.957
2024-01-20	1575	1769.127	1453.332	2084.921
2024-01-27	1525	1780.396	1414.738	2146.054

TABLE 11
Forecasting Value of The ARIMA (3,1,2)

Date	Actual Data	Predicted Data	Lower Bound	Upper Bound
2024-01-06	1625	1732.657	1563.269	1902.045
2024-01-13	1645	1735.091	1492.344	1977.839
2024-01-20	1575	1731.773	1395.129	2068.416
2024-01-27	1525	1722.655	1320.37	2124.939

TABLE 12
Forecasting Value of The ARIMA (4,1,0)

Date	Actual Data	Predicted Data	Lower Bound	Upper Bound
2024-01-06	1625	1721.85	1551.624	1892.077
2024-01-13	1645	1718.196	1473.198	1963.195
2024-01-20	1575	1714.823	1377.81	2051.836
2024-01-27	1525	1711.278	1312.813	2109.744

TABLE 13
Forecasting Value of The ARIMA (4,1,1)

Date	Actual Data	Predicted Data	Lower Bound	Upper Bound
2024-01-06	1625	1721.311	1551.439	1891.183
2024-01-13	1645	1718.737	1475.666	1961.807
2024-01-20	1575	1715.633	1382.792	2048.474
2024-01-27	1525	1710.892	1317.529	2104.254

TABLE 14
Forecasting Value of The ARIMA (4,1,2)

Date	Actual Data	Predicted Data	Lower Bound	Upper Bound
2024-01-06	1625	1717.205	1547.074	1887.336
2024-01-13	1645	1725.971	1484.02	1967.922

2024-01-20	1575	1738.84	1409.781	2067.913
2024-01-27	1525	1744.34	1351.777	2136.903

Based on forecasting value on TABLE 5, TABLE 6, TABLE 7, TABLE 8, TABLE 9, TABLE 10, TABLE 11, TABLE 12, TABLE 13, and TABLE 14, the best model for forecasting using ARIMA method can be determined by comparing the error among models as shown below.

TABLE 15
Error Measured from ARIMA Models

Model ARIMA	MSE	RMSE	MAE	MAPE
ARIMA (0,1,2)	19941.5672	141.214614	133.38025	8.47%
ARIMA (1,1,2)	20166.12962	142.0074985	134.18025	8.52%
ARIMA (2,1,0)	17890.60114	133.7557518	124.8495	7.94%
ARIMA (2,1,1)	17543.83381	132.4531382	123.6725	7.86%
ARIMA (3,1,0)	16710.11575	129.2676129	120.83725	7.68%
ARIMA (3,1,1)	31468.9419	177.3948756	165.9345	10.54%
ARIMA (3,1,2)	20837.92262	144.3534642	138.044	8.75%
ARIMA (4,1,0)	17246.88538	131.3273977	124.03675	7.88%
ARIMA (4,1,1)	17261.60756	131.3834372	124.14325	7.88%
ARIMA (4,1,2)	22502.91152	150.0097047	139.089	8.85%

TABLE 15 shows that the ARIMA (3,1,0) model achieved the lowest error among the ARIMA models considered, indicating that ARIMA (3,1,0) is the most effective model for forecasting the stock price of PT Aneka Tambang Tbk. Refers to TABLE 3, the best model that is ARIMA (3,1,0) can be expressed in the form of equation as shown below.

$$W_t = 0.0665W_{t-1} + 0.2706W_{t-2} - 0.1489W_{t-3} + e_t \tag{9}$$

Let

$$W_t = Y_t - Y_{t-1}$$

Then the equation become

$$Y_t - Y_{t-1} = 0.0665(Y_{t-1} - Y_{t-2}) + 0.2706(Y_{t-2} - Y_{t-3}) - 0.1489(Y_{t-3} - Y_{t-4}) + e_t$$
$$Y_t = Y_{t-1} + 0.0665Y_{t-1} - 0.0665Y_{t-2} + 0.2706Y_{t-2} - 0.2706Y_{t-3} - 0.1489Y_{t-3} + 0.1489Y_{t-4} + e_t$$
$$\boldsymbol{Y_t = 1.0665Y_{t-1} + 0.2041Y_{t-2} - 0.4195Y_{t-3} + 0.1489Y_{t-4} + e_t} \tag{10}$$

The accuracy of this model, demonstrated by a Mean Absolute Percentage Error (MAPE) of 7.68%, underscores its reliability for predicting future stock prices [12]. This model can be strategically utilized in investment decisions by providing investors with reliable forecasts to guide their buy or sell actions. By anticipating stock price movements with a low error rate, investors can optimize their portfolios, manage risks more effectively, and enhance overall investment performance. Additionally, companies can leverage these forecasts for financial planning and strategic decision-making, ensuring that their operations align with expected market trends.

Figure 7 below shows the visualization plot of forecasting from ARIMA (3,1,0) of PT Aneka Tambang Tbk stock price forecasting from January 6, 2024 to January 27, 2024.

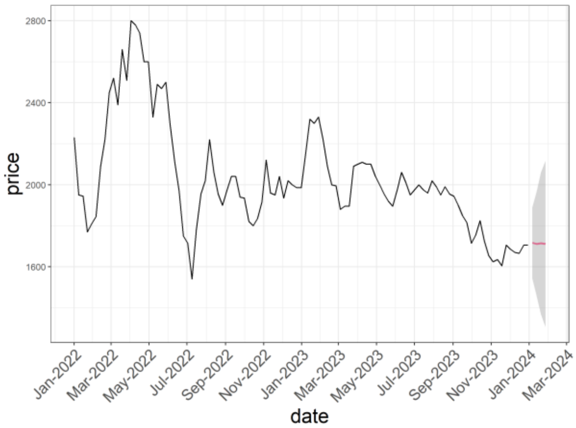

Figure. 6 Forecasting Plot from ARIMA (3,1,0)

V. CONCLUSION

Stock price forecasting has been done for PT Aneka Tambang Tbk (ANTM.JK) for the next 4 weeks from January 6, 2024 to January 27, 2024 with original stock price data from January 01, 2022 to December 31, 2023 with total 105 data obtained from Yahoo Finance website. Using Box-Jenkins Method and processed using R Studio, it was found that the ARIMA (3,1,0) model passed the residual test and has the smallest error to be used to forecast stock price and can be expressed in the following equation.

$$Y_t = 1.0665Y_{t-1} + 0.2041Y_{t-2} - 0.4195Y_{t-3} + 0.1489Y_{t-4} + e_t$$

However, it is important to note that while the ARIMA model provides adequate results, there are limitations that should be considered. One such limitation is its ability to handle unexpected market fluctuations. The model relies solely on historical data and does not account for external variables that may influence stock prices. As a next step, it would be worthwhile to consider using other models such as ARIMAX if there are significant external variables that could impact stock prices, in order to improve the accuracy of the forecast.

REFERENCES

[1] A. N. Fadila and C. Nuswandari, "Apa Saja Faktor – Faktor Yang Mempengaruhi Harga Saham?," *Jurnal Ilmiah Ekonomi dan Bisnis,* vol. 15, no. 2, pp. 283-293, 2022.

[2] I. Svetunkov, Forecasting and Analytics with the Augmented Dynamic Adaptive Model (ADAM), New York: Chapman and Hall/CRC, 2023.

[3] P. A. T. Tbk, "Sekilas ANTAM," PT Aneka Tambang Tbk, [Online]. Available: https://www.antam.com/id/about. [Accessed 24 April 2024].

[4] Y. I. Triputra, S. and S. Yurinanda, "Penerapan Metode ARIMA Box-Jenkins untuk Memprediksi Harga Saham di PT Aneka Tambang Tbk," *Prismatika: Jurnal Pendidikan dan Riset Matematika,* vol. 5, no. 2, pp. 257-273, 2023.

[5] M. N. Alim, "Pemodelan Time Series Data Saham LQ45 dengan Algoritma LSTM, RNN, dan Arima," *PRISMA, Prosiding Seminar Nasional Matematika XVI,* vol. 6, pp. 694-701, 2023.

[6] E. G. Manurung and E. S. Nugraha, "Forecasting the Weekly Stock Price of PT. OCBC NISP Tbk. using Auto Regressive Integrated Moving Average," *Journal of Actuarial, Finance, and Risk Management,* vol. 2, no. 2, pp. 24-35, 2023.

[7] A. Olivia and E. S. Nugraha, "Forecasting PT Bank Central Asia Tbk Stock Price Using ARIMA Model," *Journal of Actuarial, Finance and Risk Management (JAFRM),* vol. 2, no. 1, pp. 20-27, 2023.

[8] G. M. Singgih and E. S. Nugraha, "Forecasting the Monthly Stock Price per Share of Taiwan Semiconductor Manufacturing Company Limited (TSMC) using ARIMA Box-Jenkins Method," *Journal of Actuarial, Finance and Risk Management (JAFRM),* vol. 2, no. 1, pp. 1-9, 2023.

[9] G. E. P. Box, G. M. Jenkins and G. C. Reinsel, Time series analysis: forecasting and control, New Jersey: Prentice-Hall International , 1994.

[10] J. D. Cryer and K. S. Chan, Time Series Analysis With Applications in R, Iowa City: Springer, 2008.

[11] Kadir and O. R. Prasetyo, "Peramalan Luas Panen Padi Indonesia dengan Model ETS(Error, Trend, Seasonal)," *Jurnal Matematika dan Statistika serta Aplikasinya,* vol. 9, no. 1, pp. 7-15, 2021.

[12] P.-C. Chang, Y.-W. Wang and C.-H. Liu, "The development of a weighted evolving fuzzy neural network for PCB sales forecasting," *Expert Systems with Applications,* vol. 32, no. 1, pp. 86-96, 2007.