Journal of Actuarial, Finance and Risk Management (JAFRM)
e-ISSN:28303938
Vol. 4(1), Juni, 2025
http://e-journal.president.ac.id/presunivojs/index.php/JAFRM/index

Application of ARIMA Modeling to forecast the Weekly Stock Price per Share of (Persero) PT Telekomunikasi Indonesia Tbk

Jocelyn Beatrice Mihardja[1*]

[1,2] *Study Program of Actuarial Science, School of Business, President University, 17550, Indonesia*
[*]*Corresponding author: jocelyn.mihardja@student.president.ac.id*

Receive:April 30, 2025, Revised: July 6, 2025, Accepted: July 11, 2025

Abstract— This research is aimed to forecast the weekly stock price of PT Telkom using the ARIMA modeling approach. The dataset used in this study spanned from May 02, 2022 to January 30, 2023. The ARIMA(3,2,1) model was found to be the best fit for the data. The model's formula was $Y_t = -0.7692\,Y_{t-1} - 7409\,Y_{t-2} - 0.5175\,Y_{t-3} + e_t - 0.2444\,e_{t-1}$, where Yt represents the stock price at time t and e_t represents the residual error at time t. This model was used to predict the stock price for the next 8 weeks. The accuracy of the chosen model is 85005.53, 0.0899, 353.67, and 8.99% respectively to MSE, RMSE, MAE, and MAPE. The forecasted results showed a gradual upward trend in the stock price with some fluctuations, indicating a positive outlook for PT Telkom in the coming weeks.

Keywords— ARIMA; Forecast; PT Telekomunikasi Indonesia Tbk.; Telecommunication; Stock Market

I. INTRODUCTION

A stock, also known as equity, is a security that represents the ownership of a fraction of the issuing corporation [1]. It is a profit with a small degree of failure or risk. Because of this investors must have thoroughness and make an assessment of a company that might be a place to buy the stock, then from that the assessment needed a way to predict how the situation prices shares in the company, because this way is useful and reduces the risk for investors to invest. To predict a movement of shares in a company performed with the use of ARIMA and Artificial Neural Network. In researchers previous research, the ARIMA model and methods Artificial Neural Networks has been widely implemented to predict a movement stocks, such as (Bachtiar, 2013) [2] which discusses comparisons forecasting stock price with approach Artificial Neural Network and the Box Method - Jenkins ARIMA, and (Yaseen, 2013) [3] which discusses about the comparison of ARIMA models and Artificial Neural Networks.

PT Telekomunikasi Indonesia, Tbk is an information and communication company as well as a complete telecommunications service and network provider in Indonesia. PT. Telkom, Tbk is one of the BUMNs whose shares are currently owned by the Government of Indonesia by 52.74% and the rest by the public. In 2007 the world economy was shaken by the global economic crisis that started with the superpower, namely America, and its impact was increasingly being felt in 2008 [4].

Forecasting PT. Telekomunikasi Indonesia (Telkom) is intriguing because of its position as the most important telecommunications enterprise in Indonesia. As a primary participant in the use of a verbal exchange industry, Telkom's inventory performance holds vast implications for the general financial landscape and technological improvements inside Indonesia. The dynamic nature of the telecommunications enterprise, continuously fashioned by using improvements in generation and converting client conduct, makes forecasting Telkom's inventory an important endeavor for buyers and analysts seeking to make informed decisions and live in advance within the hastily evolving Indonesian market.

ARIMA (AutoRegressive Integrated Moving Average) model is used for forecasting because of its effectiveness in dealing with time collection records with clean styles and trends. ARIMA is an effective and extensively used method for time collection forecasting, particularly whilst handling stationary information, wherein the statistical houses stay consistent through the years. The model's capacity to capture autoregressive and moving average additives lets in it to account for the inherent dependencies inside the information, making it appropriate for programs in which beyond observations have an impact on future values. Additionally, ARIMA is noticeably truthful to enforce and interpret, making it a practical desire for my forecasting wishes. While different models like exponential smoothing or machine learning algorithms have their merits, ARIMA stood out for its simplicity, robustness, and verified track record in appropriately predicting destiny values primarily based on historic styles.

(Djoni Hatidja, 2011) [5] conducted a prediction on the stock price of PT Telkom using a time series method. The most appropriate method for forecasting the Telkom stock price is ARIMA (3,1,3) using data from January 2010 to March 2011 to predict the stock price of May to June 2011 with the prediction stock price ranging from Rp. 7,099 to Rp. 7,282. (Dona Ayu Rezaldi and Sugiman Sugiman, 2021) [6] also conducted a stock price prediction with ARIMA (0,2,1) using data from June 2013 to May 2020 to forecast the price from June 2020 to May 2021. The stock price prediction results, ranging from Rp. 2,511 to Rp. 3,056. (Andri Faisal, 2021) [7] used data from August 2020 to August 2021. From the very flat line plot result, it shows a tendency for the stock price of TLKM to remain flat or there is no significant change in the stock price. Based on the forecast, it can be seen that the lowest stock price is 2882.85 and the highest is 3580.553.

II. LITERATURE REVIEW

A. Time Series Model

The Time Series analysis is a statistical method which is used to analyze and interpret data that is collected over a period of time, showing how the variable changes over time [8]. In time series analysis, the data points are ordered chronologically to study the patterns, trends, and behavior of the data over time. The models of time series analysis includes classification, curve fitting, descriptive analysis, explorative analysis, exploratory analysis, forecasting, intervention analysis and segmentation. We will only focus on forecasting for this research.

Time series models are statistical models that are specifically designed for analyzing and forecasting data that changes over time. Types of time series models;

1. Autoregressive (AR) Model

The AR model assumes that the current value (Y_t) of a time series is dependent on previous values ($Y_{t-1}, Y_{t-2}, Y_{t-3}$, ...). This relationship, represented as AR(p), can be expressed as:

$$Y_t = c + \Sigma\ (\phi_i Y_{t-i}) + e_t \quad (1)$$

In this model, c is a constant, ϕ_i represents the autoregressive coefficients, and e_t stands for the error term at time t.

2. Moving Average (MA) Model

The MA model is a model where the time series' value at a given time (Y_t) is modeled as a linear combination of its past error terms (e_{t-i}). This relationship, represented as MA(q), can be expressed as:

$$Y_t = c + e_t + \Sigma\ (\theta_i e_{t-i}) \quad (2)$$

In this formula, Y_t represents the value of the time series at time t, c is the constant term or intercept, e_t is the error term at time t, and θ_i are the moving average coefficients for lags i from 1 to q.

3. Autoregressive Integrated Moving Average (ARIMA) Model

ARIMA is a time series model that includes three main components: autoregressive (AR), integrated (I), and moving average (MA). The formula ARIMA (p, d, q) can be expressed as :

$$W_t = \nabla^d Y_t$$

$$W_t = \phi_1 W_{t-1} + \phi_2 W_{t-2} + \cdots + \phi_p W_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q} \quad (3)$$

$$Y_t = c + \Sigma\,(\phi_i Y_{t-i}) + e_t + \Sigma\,(\theta_i e_{t-i}) \quad (4)$$

where d is the order of differencing that determines the number of times the time series needs to be differenced to achieve stationarity.

B. Autocorrelation function (ACF) and Partial Autocorrelation function (PACF)

ACF is a value between -1 and 1. If the value of ACF is closer to 1, it shows a stronger positive correlation between the values at lag h, but if the values are closer to -1, then it shows a stronger negative correlation [9]. And when the value is close to 0, it shows that there is no correlation. The autocorrelation function (ACF) of $\{X_t\}$ at lag h is;

$$ACF(h) = Cor(X_t, X_{t-h}) - [\frac{\mu(X_t)\mu(X_{t-h})}{Var(X_t)}] \quad (5)$$

Both ACF and PACF are used to identify the order of ARMA and ARIMA models. By examining the ACF and PACF plots, we can determine the values of p, d, and q in the ARIMA model. ACF measures the correlation between an observation in a time series with previous observations at different lags. PACF measures the correlation between an observation in a time series with previous observations at a specific lag, removing the effect of the intermediate observations.

The figures below illustrate the ACF and PACF plot for certain stationary time series data. The ACF plot shows a gradual decrease, while the PACF plot shows an immediate drop after one lag.

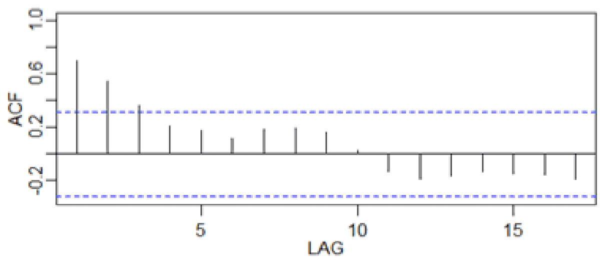

Figure. 1 ACF of time series

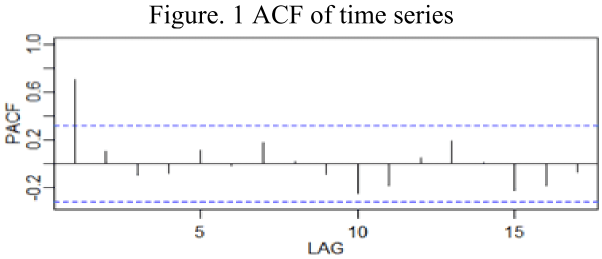

Figure. 2 PACF of time series [10]

C. Stationary Time Series

As we will be using ARIMA modeling in this forecast research, we will focus on a stationary time series, one whose statistical properties remain constant over time. A time series $\{X_t, t = 0, \pm 1, \ldots\}$ is considered stationary if the following condition is satisfied ;

1. Constant Mean : The mean of the time series remains constant over time.

Expressed as;

$$E(X_t) = \mu_X(t) \tag{6}$$

where X_t is the value of the time series at time t, and μ is a constant.

2. Constant Variance : The variance of the time series remains constant over time.
Expressed as;

$$Var(X_t) = \sigma^2 \tag{7}$$

where X_t is the value of the time series at time t, and σ^2 is a constant.

3. Constant Autocovariance : The autocovariance between any two observations of the time series remains constant over time.
Expressed as;

$$\gamma_X(x, x+h) = Cov(X_x, X_{x+h}) = Y_h = E[(X_x - \mu_X(x))(X_{x+h} - \mu_X(x+h))] \tag{8}$$

where X_t and X_{t+h} are the values of the time series at times t and $t+h$ respectively, $Cov()$ represents the covariance, Y_h is a constant that depends only on the time lag h, and it does not depend on time t.

Stationarity is an important assumption in ARIMA modeling because ARIMA models are based on the assumption that the underlying time series is stationary. If the time series is not stationary, then it may exhibit trend, seasonality, or other time-varying patterns, which can affect the modeling results and make the model less reliable for forecasting.

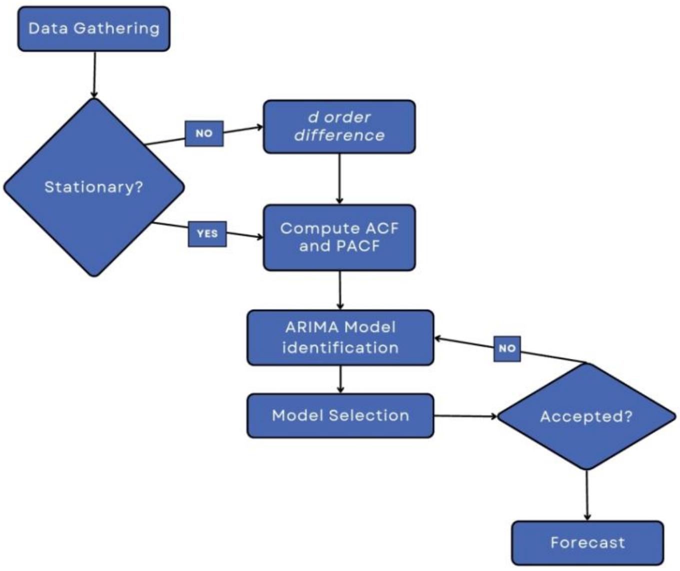

Figure. 3 Box-Jenkins Methodology Flowchart

D. Forecasting

Forecasting is a technique that uses historical data as inputs to make informed estimates that are predictive in determining the direction of future trends.

E. Estimated Error Value

There are four types of parameters to measure the error value in actual data and predictive data.

1) *Mean Absolute Error (MAE)*

MAE measures the average magnitude of the errors in a set of forecasts, without considering their direction [11]. It measures accuracy for continuous variables, the average absolute difference between the actual values and the predicted values. The formula for MAE is ;

$$MAE = \frac{1}{n} * \sum |Actual - Forecast| \tag{9}$$

2) *Mean Square Error (MSE)*

MSE measures the amount of error in statistical models. It assesses the average squared difference between the observed and predicted values [12]. When a model has no error, the MSE equals zero. As model error increases, its value increases. The mean squared error is also known as the mean squared deviation (MSD). The formula for MSE is ;

$$MSE = \frac{1}{n} * \sum (Actual - Forecast)^2 \tag{10}$$

3) *Root Mean Square Error (RMSE)*

RMSE is a measure of the deviation of a set of data points from their mean value. It is often used as a measure of accuracy or precision [13]. The RMSE is calculated by taking the square root of the sum of the squares of the deviations of the data points from their mean value. The formula for RMSE is ;

$$RMSE = \sqrt{MSE} \tag{11}$$

4) *Mean Absolute Percent Error (MAPE)*

MAPE is a metric used to define the accuracy of a forecasting method. It represents the average of the absolute percentage errors of each entry in a dataset to calculate how accurate the forecasted quantities were in comparison with the actual quantities [14]. The formula for MAPE is;

$$MAPE = \frac{1}{n} * \sum \frac{|Actual - Prediction|}{|Actual|} * 100\% \tag{12}$$

According to Lewis (1982) [17], MAPE values can be interpreted using the following general guidelines:

MAPE values	Interpretation
<10%	Highly accurate forecasting
10-20%	Good forecasting
20-50%	Reasonable forecasting
>50%	Inaccurate Forecasting

III. Analysis and Discussion

A. Data Selection

To support this forecasting research, several R packages were utilized for data processing and analysis. The **forecast** package was employed for time series forecasting, offering tools for automatic ARIMA modeling, exponential smoothing, dynamic regression models, and state space models. It also provided functions to visualize forecast results and evaluate forecasting accuracy. The **TSA** package supported the modeling and diagnostic testing of time series data, including the generation of ACF and PACF plots, which are crucial for ARIMA model selection. Additionally, the **tseries** package was used to perform the Augmented Dickey-Fuller (ADF) Test, an important step in assessing the stationarity of the dataset.

The **readr** package facilitated the efficient import of the stock price data in CSV format into R Studio, ensuring smooth data handling. The dataset used in this research consisted of the weekly stock price per share of PT Telekomunikasi Indonesia Tbk, spanning from May 2, 2022, to January 30, 2023, totaling 40 data points [15]. Finally, **ggplot2** was employed to create detailed visualizations, helping to identify trends, fluctuations, and stationarity within the time series.

TABLE 1.
THE WEEKLY STOCK PRICE PER SHARE OF PT. TELEKOMUNIKASI INDONESIA TBK.

Date	Price	Date	Price	Date	Price	Date	Price
2022-05-02	4620	2022-07-11	4100	2022-09-19	4460	2022-11-28	4030
2022-05-09	4560	2022-07-18	4110	2022-09-26	4390	2022-12-05	3980
2022-05-16	4250	2022-07-25	4240	2022-10-03	4460	2022-12-12	3670
2022-05-23	4160	2022-08-01	4230	2022-10-10	4340	2022-12-19	3740
2022-05-30	4340	2022-08-08	4700	2022-10-17	4200	2022-12-26	3780
2022-06-06	4310	2022-08-15	4540	2022-10-24	4380	2023-01-02	3750
2022-06-13	3950	2022-08-22	4550	2022-10-31	4460	2023-01-09	3730
2022-06-20	4050	2022-08-29	4370	2022-11-07	4250	2023-01-16	3780
2022-06-27	4110	2022-09-05	4560	2022-11-14	4090	2023-01-23	3890
2022-07-04	4020	2022-09-12	4600	2022-11-21	4020	2023-01-30	3960

The following code is used to plot the data on a graph. This will facilitate the identification of patterns and trends, which can help in determining the appropriate time series model for forecasting the data.

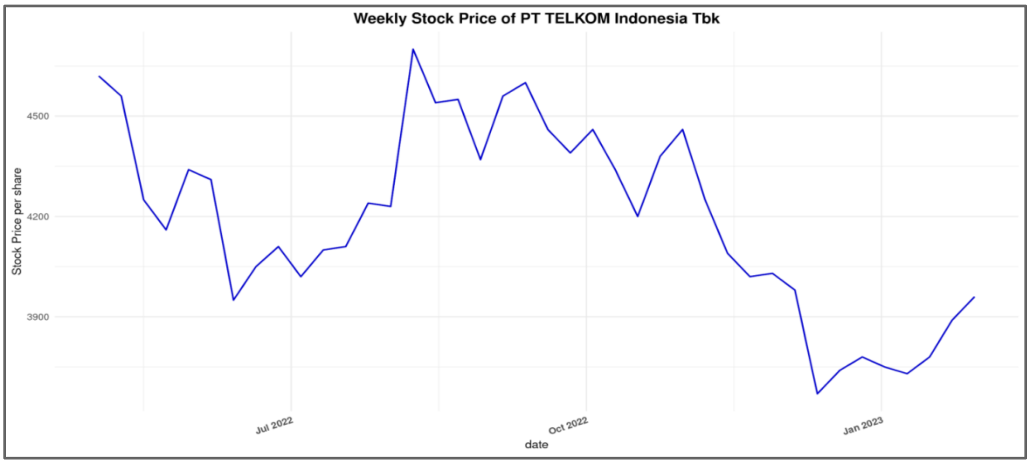

Figure. 4 Plot of Weekly Stock Price of PT. TELKOM Indonesia Tbk.

B. Stationarity Check

Augmented Dickey-Fuller (ADF) Test: The ADF test is a commonly used statistical test to determine the stationarity of a time series data in R [16]. The result of the ADF test will be considered depending on its p-value, where when it exceeds 0.01, the differencing process is necessary to do.

After running the selected data through the ADF test, the result shows the p-value to be greater than 0.05 which can be concluded as not stationary. This data then has to undergo the differencing, "diff(data)" function to make it stationary.

After performing the first differencing, the ADF test was repeated. However, the p-value obtained was 0.5751, which still exceeded the 0.05 threshold. This result suggested that the data remained non-stationary and that a second differencing was required.

Following the second differencing, the ADF test was conducted once more. This time, the p-value dropped to exactly 0.01, which confirmed that the series had become stationary. Therefore, the differencing order for the ARIMA model was determined to be **d = 2**. Here is the graph plot after the second differentiation.

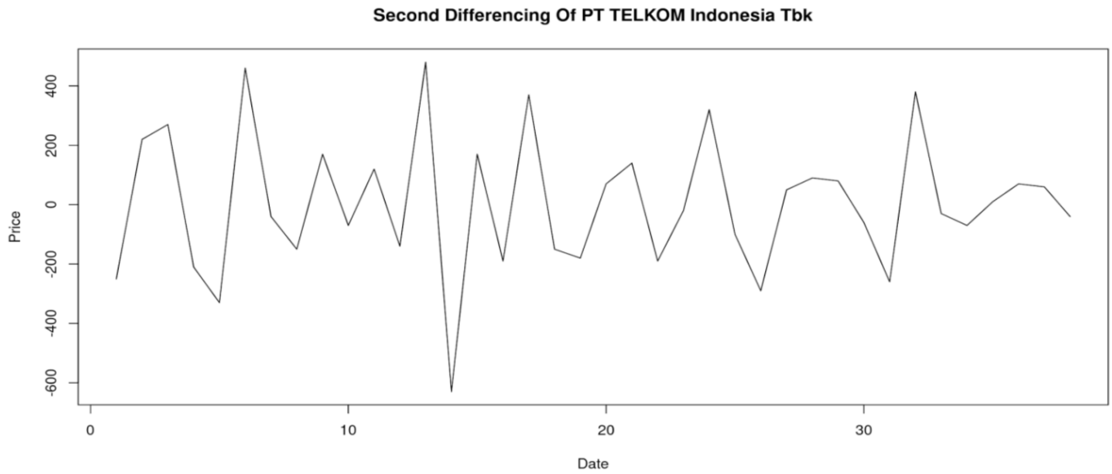

Figure. 7 The Second Differencing plot of PT TELKOM Indonesia Tbk

C. Data Exploration

The data will then be plotted to autocorrelation plot (ACF) and partial autocorrelation plot (PACF) to find the value p, d and q, which is necessary for the ARIMA Model selection process.

The image on the left shows the PACF plot experiencing a sharp increase after the lag p is 3, so the p value is 3. The image on the right shows the ACF plot also experienced a significant increase after the lag q, so the value of q is 4.

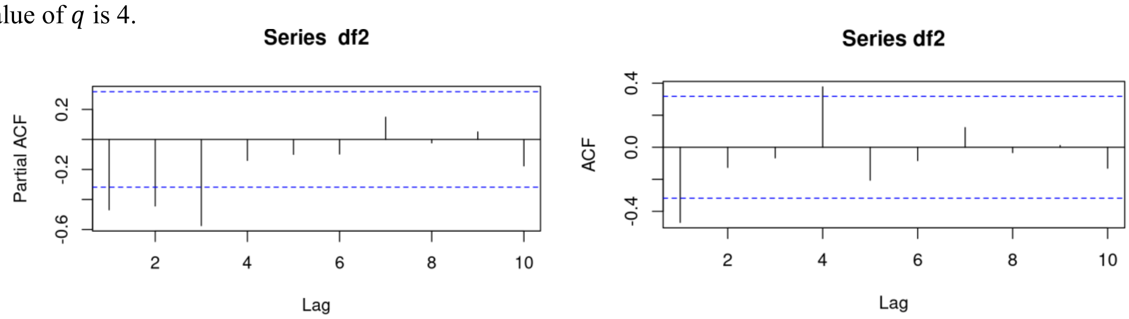

Figure. 8 PACF and ACF Plot of df2

As shown on the plot above, this data has ARIMA(3,2,4) with the equation;

ARIMA(3,2,4) is ARMA(3,4) with d=2. (13)

$$W_t = \phi_1 W_{t-1} + \phi_2 W_{t-2} + \phi_3 W_{t-3} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \theta_3 e_{t-3} - \theta_4 e_{t-4}$$

Where ;

$W_t = Y_t - 2Y_{t-1} + Y_{t-2}$

$W_{t-1} = Y_{t-1} - 2Y_{t-2} + Y_{t-3}$

$W_{t-2} = Y_{t-2} - 2Y_{t-3} + Y_{t-4}$

$W_{t-3} = Y_{t-3} - 2Y_{t-4} + Y_{t-5}$

so,

$$Y_t = (\phi_1 + 2)Y_{t-1} + (\phi_2 - 2\phi_1 - 1)Y_{t-2} + (\phi_1 - 2\phi_2 + \phi_3)Y_{t-3} + (\phi_2 - 2\phi_3)Y_{t-4} + \phi_3 Y_{t-5} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \theta_3 e_{t-3} - \theta_4 e_{t-4}$$

Here are the ARIMA models that can be built;

TABLE 2
ARIMA MODELS

ARIMA Model	p	d	q
ARIMA(3,2,4)	3	2	4

Journal of Actuarial, Finance and Risk Management (JAFRM)
e-ISSN:28303938
Vol. 4(1), Juni, 2025
http://e-journal.president.ac.id/presunivojs/index.php/JAFRM/index

ARIMA(3,2,3)	3	2	3
ARIMA(3,2,2)	3	2	2
ARIMA(3,2,1)	3	2	1
ARIMA(3,2,0)	3	2	0
ARIMA(2,2,4)	2	2	4
ARIMA(2,2,3)	2	2	3
ARIMA(2,2,2)	2	2	2
ARIMA(2,2,1)	2	2	1
ARIMA(2,2,0)	2	2	0
ARIMA(1,2,4)	1	2	4
ARIMA(1,2,3)	1	2	3
ARIMA(1,2,2)	1	2	2
ARIMA(1,2,1)	1	2	1
ARIMA(1,2,0)	1	2	0
ARIMA(0,2,4)	0	2	4
ARIMA(0,2,3)	0	2	3
ARIMA(0,2,2)	0	2	2
ARIMA(0,2,1)	0	2	1

D. Parameter Estimation

Estimation of parameters ϕ_p of autoregressive (AR) function and θ_q the moving average (MA) function in each model can be found by looking at the summary of each model.

After executing this function, we can find the values of AR1 to AR3, MA1 to MA4, Log Likelihood, and AIC that will be considered to choose the best ARIMA model.

The table below is the result of parameter estimation for each model.

TABLE 3
PARAMETER ESTIMATION SUMMARY

ARIMA Model	**AR1**	**AR2**	**AR3**	**MA1**	**MA2**	**MA3**	**MA4**	**MSE**	**Log Likelihood**	**AIC**
ARIMA(3,2,4)	-0.7882	-0.7064	-0.3887	-0.1981	-0.0322	-0.0754	0.2211	20722	-243.83	503.65
ARIMA(3,2,3)	-0.8149	-0.8128	-0.5177	-0.1874	0.0219	-0.1009	-	20989	-244.04	502.09
ARIMA(3,2,2)	-0.7788	-0.7405	-0.5188	-0.2339	-0.0130	-	-	21032	-244.07	500.14
ARIMA(3,2,1)	-0.7692	-0.7409	-0.5175	-0.2444	-	-	-	21033	-243.07	498.14
ARIMA(3,2,0)	-0.9244	-0.8426	-0.5822	-	-	-	-	21509	-244.44	496.88
ARIMA(2,2,4)	-1.005	-0.4729	-	0.1920	-0.4428	-0.4266	0.5948	19019	-243.67	501.35
ARIMA(2,2,3)	0.3041	-0.5738	-	-1.3641	0.9436	-0.2466	-	22213	-245.06	502.12
ARIMA(2,2,2)	0.1329	-0.4481	-	-1.1480	0.5940	-	-	22657	-245.43	500.86
ARIMA(2,2,1)	-0.2675	-0.3227	-	-0.7282	-	-	-	24583	-246.83	501.65
ARIMA(2,2,0)	-0.6729	-0.4324	-	-	-	-	-	33119	-252.00	510.00
ARIMA(1,2,4)	-0.6025	-	-	-0.2751	-0.5424	-0.0137	0.3650	23714	-246.12	504.24
ARIMA(1,2,3)	-0.0597	-	-	-0.9638	0.0567	0.2256	-	24744	-246.86	503.72
ARIMA(1,2,2)	-0.7661	-	-	-0.2616	-0.7383	-	-	24252	-247.60	503.19
ARIMA(1,2,1)	-0.787	-	-	-1.0000	-	-	-	24074	-247.52	501.04
ARIMA(1,2,0)	-0.4709	-	-	-	-	-	-	41342	-256.01	516.02
ARIMA(0,2,4)	-	-	-	-1.1159	0.1970	0.3183	-0.1367	24468	-246.75	503.50
ARIMA(0,2,3)	-	-	-	-1.0943	-0.0110	0.1053	-	23400	-247.13	502.26
ARIMA(0,2,2)	-	-	-	-1.1211	0.1211	-	-	23923	-247.45	500.91
ARIMA(0,2,1)	-	-	-	-1.0000	-	-	-	24322	-247.63	499.27

E. Model Selection and Evaluation

To find the best fit ARIMA model, residual analysis was performed on each fitted model. The Shapiro-Wilk Test and Ljung-Box Test were used to assess the residuals. A good ARIMA model will have residuals that are normally distributed, with a constant mean and variance, and no significant autocorrelation or seasonality.

The result of each model analysis summary

TABLE 4
RESIDUAL ANALYSIS SUMMARY

ARIMA Model	Shapiro Test	Ljung-Box Test	AIC	Accepted
ARIMA(3,2,4)	0.9727	0.8601	503.65	Yes
ARIMA(3,2,3)	0.6403	0.8788	502.09	Yes
ARIMA(3,2,2)	0.6247	0.9030	500.14	Yes
ARIMA(3,2,1)	**0.6171**	**0.9087**	**498.14**	**Yes**
ARIMA(3,2,0)	**0.8419**	**0.5514**	**496.88**	**Yes**
ARIMA(2,2,4)	0.4140	0.7332	501.35	No
ARIMA(2,2,3)	0.5713	0.8870	502.12	Yes
ARIMA(2,2,2)	0.3482	0.6729	500.86	No
ARIMA(2,2,1)	0.1764	0.5797	501.65	No
ARIMA(2,2,0)	0.5162	0.1022	510.00	No
ARIMA(1,2,4)	0.5624	0.5478	504.24	Yes
ARIMA(1,2,3)	0.5632	0.8892	503.72	Yes
ARIMA(1,2,2)	0.3763	0.6277	503.19	No
ARIMA(1,2,1)	0.3053	0.8008	501.04	No
ARIMA(1,2,0)	0.8502	0.1767	516.02	No
ARIMA(0,2,4)	0.3511	0.8399	503.50	No
ARIMA(0,2,3)	0.2035	0.8405	502.26	No
ARIMA(0,2,2)	0.2522	0.9764	500.91	No
ARIMA(0,2,1)	0.4000	0.5036	499.27	No

Based on the residual analysis summary in Table 4, the accepted models include ARIMA(3,2,4), ARIMA(3,2,3), ARIMA(3,2,2), ARIMA(3,2,1), ARIMA(3,2,0), ARIMA(2,2,3), ARIMA(1,2,4), and ARIMA(1,2,3). From those, ARIMA(3,2,1) was selected as the final model because it passed both residual tests — with a Shapiro-Wilk value of 0.6171 and Ljung-Box value of 0.9087 — indicating that the residuals are normally distributed and independent. It also had the lowest AIC value (498.14), making it the most suitable model. This selected model was then used to compare predicted and actual stock prices using four error metrics, which are shown in Table 5: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE).

Below is a summary comparison between ARIMA(3,2,1) and another accepted model, ARIMA(3,2,0). ARIMA(3,2,1) resulted in a MAPE value of 8.99%, which according to Lewis (1982), means the model gives a highly accurate forecast (MAPE < 10%).

TABLE 5
ERROR VALUE ESTIMATION PARAMETERS COMPARISON BETWEEN MODEL 4 AND MODEL 5

ARIMA Model	MSE	RMSE	MAE	MAPE
ARIMA(3,2,1)	85005.53	0.0899	353.67	8.99%
ARIMA(3,2,0)	120201.24	0.1071	422.03	10.71%

To avoid repeating the full comparison table in this section, only a few examples are shown in table 6. The complete version can be found in **Appendix A**.

TABLE 6
FORECASTED VS. ACTUAL STOCK PRICES FOR ARIMA (3,2,1)

Date	Lower Bound	Upper Bound	Forecast	Actual Data	MSE	RMSE	MAE	MAPE
2023-02-06	3720.344	4197.440	3958.892	3860	9779.627664	0.0256196891	98.892	2.562%
2023-02-13	3675.985	4346.141	4011.063	3800	44547.58997	0.0555428947	211.063	5.554%
2023-02-20	3681.704	4508.563	4095.633	3760	112649.5107	0.0892640957	335.633	8.926%

The equation of ARIMA(3,2,1) is;

$$Y_t = 1.2308\, Y_{t-1} - 0.2025\, Y_{t-2} + 0.1951\, Y_{t-3} + 0.2941\, Y_{t-4} - 0.5175\, Y_{t-5} + e_t - 0.2444\, e_{t-1} \quad (14)$$

Here is the plot for Model 4;

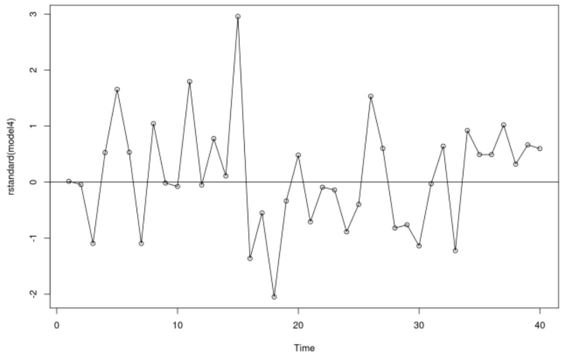

Figure. 10 Model 4 residual plot

To visually check the normality of model 4, we will use the qqnorm and qqline function. Also, using the residual of model 4 to check the ACF and PACF.

Here is the plot shown;

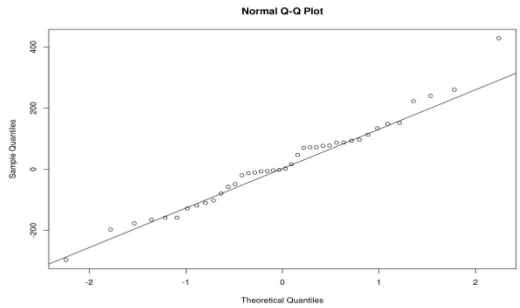

Figure. 11 Model 4 Q-Q Normal Plot

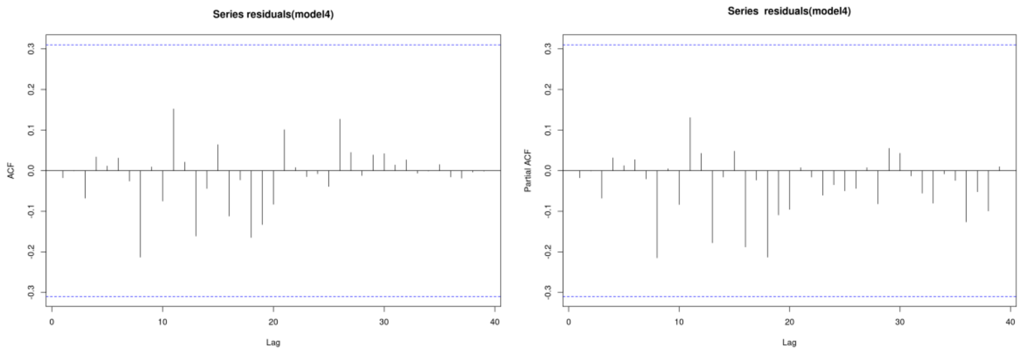

Figure. 12 Model 4 ACF dan PACF Plot

F. Forecast

The following plot shows the forecast result of the weekly price of PT Telekomunikasi Indonesia Tbk. for the next 8 weeks using model 4 ARIMA(3,2,1);

Journal of Actuarial, Finance and Risk Management (JAFRM)
e-ISSN:28303938
Vol. 4(1), Juni, 2025
http://e-journal.president.ac.id/presunivojs/index.php/JAFRM/index

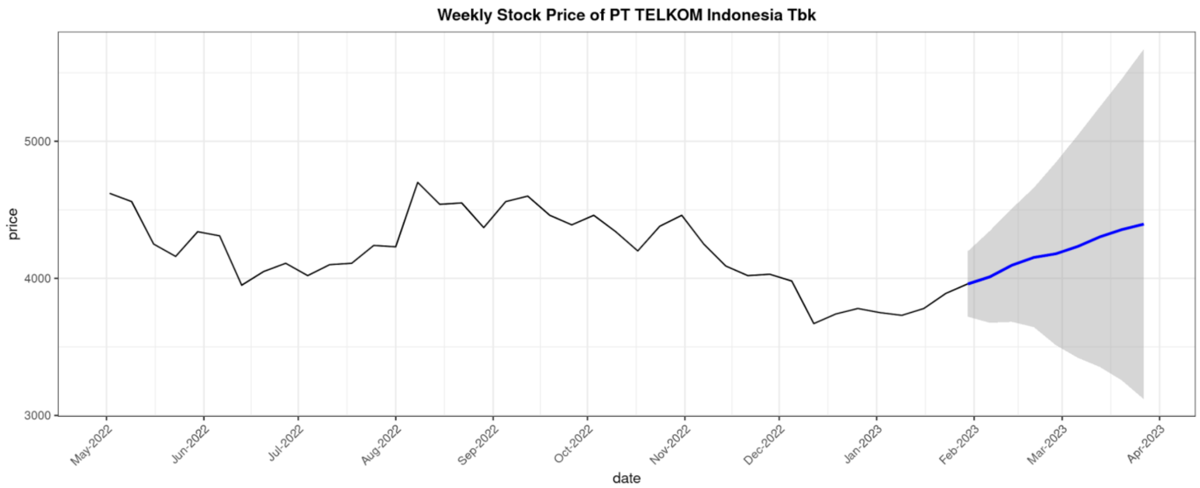

Figure. 13 Forecast Plot of Weekly Stock Price of PT TELKOM Indonesia Tbk.

IV. CONCLUSION

Based on the results of the forecast from the research above on the historical data of the weekly stock price of PT Telekomunikasi Indonesia Tbk from May 02, 2022 to January 30, 2023, it shows that Model 4 (ARIMA(3,2,1)) is the best model. This model was chosen because it had the second smallest AIC value, which is 498.14, and also passed both the Shapiro-Wilk Test and Ljung-Box Test, meaning that the residuals are normally distributed and do not show autocorrelation.

The equation of ARIMA(3,2,1) used is:

$$Y_t = 1.2308\, Y_{t-1} - 0.2025\, Y_{t-2} + 0.1951\, Y_{t-3} + 0.2941\, Y_{t-4} - 0.5175\, Y_{t-5} + e_t - 0.2444\, e_{t-1} \quad (15)$$

This model was then used to predict the stock price for the next 8 weeks. From the forecasting results, it can be seen that the stock price shows a gradual upward trend. This might reflect investor optimism, a recovering market, or positive company performance expectations, especially considering PT Telkom's role as a major telecommunications provider in Indonesia.

However, this research also has some practical limitations. The data used only includes 40 weekly stock price observations, so the model may not fully reflect long-term patterns or unexpected market events. Also, this model does not consider seasonal effects, even though seasonality might affect the telecommunications sector. Lastly, ARIMA is a model that relies on historical patterns, so it might not perform well during sudden changes like policy shifts, global news, or market shocks.

For investors or analysts, this research can help as a starting point for making short-term predictions and decisions using time series analysis. However, the results should still be supported by more recent data, and combined with external analysis such as company news, economic outlook, or industry trends.

As a recommendation for future research, it is suggested to:

- Try using SARIMA to consider seasonal effects that might be present,
- Explore hybrid models that combine ARIMA with machine learning techniques such as neural networks,
- Use a longer or updated dataset to improve the accuracy and reliability of the forecast results.

Through these improvements, forecasting models in the future can be even more accurate and useful in analyzing stock price movements in real situations.

References

[1] A. Hayes, "Stocks: What They Are, Main Types, How They Differ From Bonds," *Investopedia*, 2023. [Online]. Available: https://www.investopedia.com/terms/s/stock.asp. [Accessed 27 April 2024].

[2] S. Bachtiar, "Penerapan Model Pembelajaran Problem Based Learning Untuk Meningkatkan Kemampuan Berpikir Kritis, Kesadaran Metakognitif dan Hasil Belajar Kognitif Biologi Pada Siswa Kelas XI di SMA Negeri 1 Binamu," *Test Repository*, 2013. [Online]. Available: http://eprints.unm.ac.id/2262/. [Accessed 27 April 2024].

[3] M. K. Okasha and A. A. Yaseen, "Comparison between ARIMA Models and Artificial Neural Networks in Forecasting Al-Quds Indices of Palestine," *ResearchGate*, 2013. [Online]. Available: https://www.researchgate.net/publication/258221036. [Accessed 27 April 2024].

[4] Telkom Indonesia, "About Telkomgroup," [Online]. Available: https://www.telkom.co.id/sites/about-telkom/en_US/page/profile-and-brief-history-24. [Accessed 27 April 2024].

[5] D. Hatidja, "Penerapan Model ARIMA untuk Memprediksi Harga Saham PT. Telkom Tbk," *Jurnal Ilmiah Sains*, vol. 11, no. 1, pp. xx–xx, 2011.

[6] D. A. Rezaldi and Sugiman, "Peramalan Metode ARIMA Data Saham PT. Telekomunikasi Indonesia," *PRISMA, Prosiding Seminar Nasional Matematika*, vol. 4, pp. 611–620, 2021.

[7] A. Faisal, "Prediksi Saham Telkom dengan Metode ARIMA," *Jurnal Bisnis, Logistik dan Supply Chain (BLOGCHAIN)*, vol. 1, no. 2, pp. 45–50, 2021.

[8] Tableau, "Time Series Analysis: Definition, Types, Techniques," *Tableau*, [Online]. Available: https://www.tableau.com/learn/articles/time-series-analysis. [Accessed 27 April 2024].

[9] T. Smith, "Autocorrelation: What It Is, How It Works, Tests," *Investopedia*, 2023. [Online]. Available: https://www.investopedia.com/terms/a/autocorrelation.asp. [Accessed 27 April 2024].

[10] Cross Validated, "ACF and PACF of Residuals to Determine ARIMA Model," *Stack Exchange*, [Online]. Available: https://stats.stackexchange.com/questions/380966. [Accessed 27 April 2024].

[11] J. J., "MAE and RMSE — Which Metric is Better?," *Medium*, 3 January 2021. [Online]. Available: https://medium.com/human-in-a-machine-world/mae-and-rmse-which-metric-is-better-e60ac3bde13d. [Accessed 27 April 2024].

[12] J. Frost, "Mean Squared Error (MSE)," *Statistics by Jim*, 2021. [Online]. Available: https://statisticsbyjim.com/regression/mean-squared-error-mse/. [Accessed 27 April 2024].

[13] V. Vipin, "Root Mean Square - RMSE," *Infinity Learn*, 27 December 2022. [Online]. Available: https://infinitylearn.com/surge/maths/root-mean-square/. [Accessed 27 April 2024].

[14] Indeed Editorial Team, "What is MAPE? A Guide to Mean Absolute Percentage Error," *Indeed Career Guide*, 2023. [Online]. Available: https://www.indeed.com/career-advice/career-development/what-is-mape. [Accessed 27 April 2024].

[15] Yahoo Finance, "TLKM.JK Historical Data," [Online]. Available: https://finance.yahoo.com/quote/TLKM.JK/history. [Accessed 27 April 2024].

[16] M. Chaudhary, "Why is Augmented Dickey–Fuller Test (ADF Test) so Important in Time Series Analysis," *Medium*, 14 December 2021. [Online]. Available: https://medium.com/@cmukesh8688/why-is-augmented-dickey-fuller-test-adf-test-so-important-in-time-series-analysis-6fc97c6be2f0. [Accessed 27 April 2024].

[17] C. D. Lewis, *Industrial and Business Forecasting Methods: A Radical Guide to Exponential Smoothing and Curve Fitting*. London: Butterworth Scientific, 1982.