pijmath
Pattimura International Journal of Mathematics (PIJMath)
Volume 4, issue 2, pages 87-96, Nov. 2025
E-ISSN : 2830-6791
RESEARCH ARTICLE ◙ *OPEN ACCESS*
DOI: https://doi.org/10.30985/pijmathvol4iss2p87-96

Forecasting the Stock Price of PT. Dayamitra Telekomunikasi with Single Input Transfer Function Model

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ABSTRACT

Article History

Received : June 20th, 2025
Accepted : October 27th, 2025
Published : November 29th, 2025

Keywords
Transfer function;
ARIMA;
Forecasting;
Stock Price;
Trading Volume;

The unpredictable movement of stock prices is often a challenge for investors, so it requires a deeper understanding and consideration of various factors before making investment decisions. One of the factors that affect stock price movements is trading volume. Therefore, this study uses a single input transfer function model to forecast the daily closing stock price of PT. Dayamitra Telekomunikasi, with the closing stock price as the output variable and the stock trading volume as the input variable. The transfer function is a forecasting model that integrates ARIMA with multiple regression analysis, allowing modeling not only based on the values of the output variables, but also considering the influence of the input variables. ARIMA model estimation is performed on the input series for the prewhitening process, then the order of the transfer function is determined using cross-correlation plots, as well as model diagnostic tests to ensure its feasibility. Model accuracy is calculated to evaluate its performance in forecasting. The data used in this study are daily data from the period July 5, 2022 to October 9, 2024. The transfer function model obtained has an order of (2,0,0), with a MAPE value of 1.09%, which indicates that the model has good accuracy. Based on the forecasting results, it is estimated that there will be a decrease in the share price of PT. Dayamitra Telekomunikasi Tbk for the next five periods.

[1]***How to cite this article:***

R. Arsanti, N. Satyahadewi, S. Martha, FORECASTING THE STOCK PRICE OF PT. DAYAMITRA TELEKOMUNIKASI WITH SINGLE INPUT TRANSFER FUNCTION MODEL, *Pattimura Int. J. Math. (PIJMATH).*, vol. 4, iss. 2, pp. 87 - 96, Nov. 2025.

1. Introduction

Shares can be interpreted as a sign of ownership of capital in a company. Currently, stocks have become one of the most sought-after instruments in the capital market, in line with the ease of access through various online trading platforms. Investment itself is an activity of asset or capital placement carried out with the hope of obtaining profits in the future [1]. The strong public interest in investing stems from its role as a way to allocate funds into specific assets over a defined period with the aim of earning a return [2]. With the proliferation of online stock trading applications, investing can now be done more easily and efficiently. Stocks themselves have a fluctuating nature because they continuously undergo dynamic changes, which is one of the characteristics of the capital market. The unpredictable movement of stock prices often poses a challenge for investors, making it necessary to be aware of and consider many factors before making investment decisions in stocks.

One of the factors that influence stock price movements is trading volume. The trading volume of stocks is the total number of a company's shares traded by investors at a given time [3],. The higher the trading volume, the greater the demand and supply of shares, which impacts the fluctuations in stock prices in the market [4]. Thus, trading volume can provide a positive signal regarding stock price movements [5].

By utilizing various existing models and analysis techniques, stock price forecasting is expected to anticipate market changes and assist in making better investment decisions. One of the models that can be applied is the Transfer Function. One of the time series analysis models that is frequently used for time series data forecasting procedures that include two variables—the output variable and the input variable—is the Transfer Function Model. [6]. Single input transfer function is used to predict the output variable and calculate the magnitude of the influence of the input variable on the prediction results [7].

The Single Input Transfer Function model is used in this study to examine the link between PT. Dayamitra Telekomunikasi Tbk's daily stock closing price as an output variable and its daily stock trading volume as an input variable. The purpose of this research is to develop a Single Input Transfer Function model for forecasting the stock price of PT. Dayamitra Telekomunikasi Tbk, assess the accuracy of the forecasting results obtained from the model, and forecast the company's stock price for the next five periods using the established model. Daily closing stock prices of PT. Dayamitra Telekomunikasi Tbk and daily trading volumes were gathered between July 5, 2022, and October 8, 2024, and served as the basis for this study. It is expected that the model built can provide accurate and reliable stock price predictions, so it can be used as a basis for making more precise investment decisions.

2. Research Methods

The following section presents the research on Single Input Transfer Function Modeling, introduced through a detailed account of the methodological framework.

2.1. Stationarity

Non-stationarity of variance can lead to heteroskedasticity, which has the potential to produce less accurate analysis results. One of the methods frequently used to address the issue of variance stationarity is the Box-Cox transformation. The Box-Cox transformation involves a class of single power transformations, where λ is raised to the power of the response variable Y_t, resulting in the transformation Y_t^{λ}, where λ is the parameter that requires estimation [8]. The Box-Cox transformation can generally be defined as follows [9]:

$$T(Y_t) = \begin{cases} \dfrac{Y_t^{\lambda} - 1}{\lambda} & , for\ \lambda \neq 0 \\ ln(Y_t)\, , for\ \lambda = 0 \end{cases}$$

where,

Y_t	:	The value of the output series at time t
λ	:	The transformation parameter's value

Once the data have been transformed, the next step involves examining whether the mean is stationary. For this evaluation, the Augmented Dickey-Fuller (ADF) unit root test might be used. The ADF test is an extension of the Dickey-Fuller unit root test (DF) designed to address the autocorrelation issues present in the DF test. This test is conducted with the hypothesis [10]:

H_0	:	$\phi = 1$ (there is a unit root or the data is non-stationary)
H_1	:	$\lvert\phi\rvert < 1$ (there is no unit root or the data is stationary)

The ADF test statistic can be expressed in the form of an equation:

$$ADF_{statistic} = \frac{(\hat{\phi} - 1)}{SE(\hat{\phi})}$$

where,

$\hat{\phi}$	:	Estimation of the coefficient of Y_{t-1} in the ADF regression model
$SE(\hat{\phi})$	:	Standard Error of $\hat{\phi}$

The testing criterion states that H_0 will be rejected if the calculated ADF test statistic is less than the critical value from the Dickey-Fuller distribution table at the specified significance level. When the data is identified as having a non-stationary mean, differencing may be applied to stabilize its mean and achieve stationarity. Differencing is a transformation method that can be used to make time series data stationary in the mean [11]. The differencing process is assisted by the backward shift operator (B) in order d and is formulated in the equation [12]:

$$W_t = (1 - B)^d Y_t$$

where,

W_t	:	The observation value after t differencing
B	:	Backward shift operator
d	:	Order of differencing
Y_t	:	The value of the output series at time t, $t = 0,1,2,\dots,n$
$(1 - B)^d$	:	Differencing of order d

2.2. Autoregressive Integrated Moving Average (ARIMA)

One of the forecasting techniques commonly employed in time series analysis is the ARIMA model. One kind of time series approach for non-stationary data is the ARIMA model, which blends the AR and MA models. This model is generally written in the notation ARIMA(p, d, q), where p represents the order of AR, d represents the differencing, and q represents the order of the MA process. In general, the form of the ARIMA equation is [12]:

$$\phi_p(B)(1 - B)^d Y_t = \theta_q(B) a_t$$

with,

$$\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$$
$$\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$$

where,

ϕ_p	:	The coefficient of the AR model at lag p
θ_q	:	The coefficient of the MA model at lag q
B	:	Backward shift operator
Y_t	:	The value of the output series at time t
a_t	:	Residual at time t

2.3. Prewhitening

Prewhitening is a crucial step in transfer function modeling that makes sure autocorrelation in the time series does not affect the analysis of the connection between the input and output series. The prewhitening step essentially aims to transform the input variable into a white noise process [13]. This process is applied to both the input and output series before further analysis. The prewhitening equation for the input series is [14]:

$$\alpha_t = \frac{\phi_x(B)}{\theta_x(B)} x_t \qquad (1)$$

The following formula is used to apply the prewhitening step on the output series after it has been completed on the input series [14]:

$$\beta_t = \frac{\phi_x(B)}{\theta_x(B)} y_t \qquad (2)$$

2.4. Cross-Correlation Function

In transfer function modeling, the cross-correlation function serves to determine the appropriate general structure of the model to be applied. The equation for the cross-covariance between two variables is [14]:

$$C_{\alpha\beta}(k) = \frac{1}{n} \sum_{t=1}^{n-k} (\alpha_t - \bar{\alpha})(\beta_{t+k} - \bar{\beta})$$

This function calculates the covariance between the input series (α) and toutput series (β) that have been prewhitened at a lag of k periods. The subsequent step involves computing the cross-correlation coefficient between the prewhitened input series (α) and the prewhitened output series (β). The equation for calculating the cross-correlation coefficient between α and β is:

$$\hat{\rho}_{\alpha\beta} = \frac{\left(C_{\alpha\beta}(k)\right)}{\sqrt{C_{\alpha}(0)C_{\beta}(0)}} = \frac{C_{\alpha\beta}(k)}{S_{\alpha}S_{\beta}}$$

2.5. Determination of the orders r, s, b

Three important parameters in constructing a transfer function model are (r, s, b). There are several guidelines for determining the orders r, s, and b, including the following [7]:

1. The order r is determined by observing the lag pattern that appears on the cross-correlation plot. If the plot shows a few truncated lags, then $r = 0$. If the plot displays an exponentially decreasing pattern, then $r = 1$. If the pattern is exponentially decreasing with a sinusoidal component, then $r = 2$.
2. The order s is identified by observing the lag in the ccf plot that occurs just before the onset of a decreasing pattern in the following lags.
3. The order b is determined by identifying the first lag that shows significance in the cross-correlation plot.

2.6. Single Input Transfer Function Model

The transfer function model integrates the ARIMA approach with multiple regression techniques. It is a method used to forecast future values of a time series (referred to as the output series) based on its historical data and one or more related time series (the input series) [7]. In other terms, the model considers not just the previous values of the output variable itself but also the influence of external variables that may affect its movement. Input series, along with other elements identified as disturbances or noise (n_t), is assumed to affect the output series within the framework of the transfer function [15].

The single input transfer function model forecasts future values of an output series (y_t) by utilizing both the historical values of the series itself and one influencing input series (x_t) [7]. The general equation form for a transfer function model with a one input (x_t) and a one output (y_t) is presented as follows [16]:

$$y_t = v(B)x_t + n_t$$

with,

$$v(B) = v_0 + v_1B + v_2B^2 + \cdots + v_kB^k$$

where,

y_t	:	The value of the stationary output series at time t
v	:	Impulse response weights
x_t	:	The value of the input series at time t that has been stationary
n_t	:	The noise series from the transfer function model at time t

This model may also be represented in the following form [14]:

$$y_t = \frac{\omega_S\,(B)}{\delta_r\,(B)}\,x_{t-b} + \frac{\theta_q\,(B)}{\phi_p\,(B)}\,a_t \tag{3}$$

with,

$$\omega_S(B) = \omega_0 - \omega_1B - \omega_2B^2 - \cdots - \omega_SB^S$$
$$\delta_r(B) = 1 - \delta_1B - \delta_2B^2 - \cdots - \delta_rB^r$$
$$\theta(B) = 1 - \theta_1B - \theta_2B^2 - \cdots - \theta_qB^q$$
$$\phi(B) = 1 - \phi_1B - \phi_2B^2 - \cdots - \phi_pB^p$$

2.7. Diagnostic Tests

The transfer function model also goes through a diagnostic test phase, just like the ARIMA model. This test aims to evaluate the suitability of the constructed transfer function model. The testing was conducted as follows [17]:

1. Calculating autocorrelation for the residual values (a_t) of the model.

2. Calculating CCF between α_t and a_t.

The model is suitable since there are no cross-correlation values that deviate considerably from zero, and the residual values (a_t) are random.

3. Results And Discussion

The data used to model stock price forecasting with a single input transfer function model consists of the daily closing price and the daily trading volume of PT. Dayamitra Telekomunikasi Tbk.

3.1. Stationarity

The stationarity test is performed first to determine whether adjustments are needed for the stationarity of the data. The first test conducted is the variance stationarity test using the Box-Cox method through R Studio. The test results for both variables are presented in Table 1 below.

Table 1. The value of $\boldsymbol{\lambda}$

Variable	*p-value*
X	0.0001
Y	0.0001

Based on the two lambda values, the Box-Cox variance transformation will be applied in cases where λ is not equal to zero. The variable resulting from the Box-Cox transformation will be denoted as $T(Y)$ for stock closing prices and $T(X)$ for stock trading volumes. After the Box-Cox transformation, the Augmented Dickey-Fuller (ADF) test is used to determine whether the mean is stationary or not. In this test, two hypotheses are used, namely:

H_0 : Data is non-stationary
H_1 : Data is stationary

The p-value serves as the basis for the ADF test's decision criterion. H_0 is rejected, indicating that the data is regarded as stationary in the mean, if the p-value is less than α at a significance threshold of α = 5%. The data must be differencing to become stationary if the p-value is less than or equal to α. Table 2 below displays the findings of the ADF test for both variables.

Table 2. Comparison of ADF Values Before Differencing

Variable	p-value	Decision
$T(X)$	0.076	Non-Stationary
$T(Y)$	0.010	Stationary

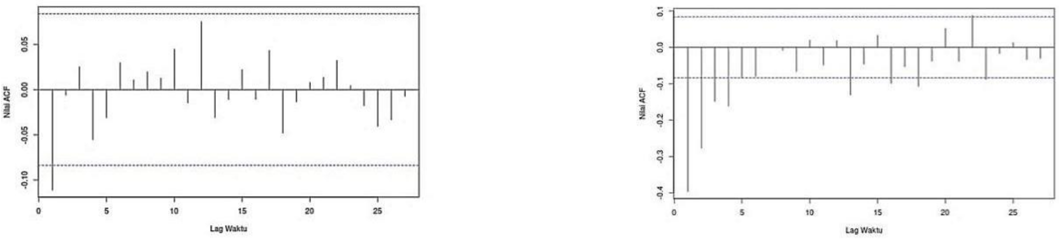
Table 2 shows that the data $T(Y)$'s mean is still non-stationary, while the data $T(X)$ has met the stationarity assumption. Therefore, the next step is to apply differencing to the data $T(Y)$ to achieve stationarity. The results of the ADF test for both variables after the differencing process are presented in Table 3 below.

Table 3. Results of the ADF Test After First Differencing

Variable	*p-value*	Decision
x	0.010	Stationary
y	0.010	Stationary

3.2. ARIMA Model for the Input Series

Finding the proper ARIMA model order for the input series (x_t) comes after the data's stationarity has been confirmed. As seen in Figure 1, the ACF and PACF plots of the series x_t are analyzed to identify the order.



(a) (b)

Figure 1. Daily Trading Volume Plot: (a) ACF and (b) PACF

The analysis of the ACF and PACF results in several candidate models that can be used. Table 4 presents various possible models along with the estimates for each parameter. Additionally, the table also shows the p-value, which is used as the basis for determining the significance of each parameter in the model.

Table 4. Several Possible ARIMA Models for the Input Series

Possible Models	Parameter Estimation Results			
	Parameter	**Coefficient**	***p-value***	**Description**
ARIMA (0,1,1)	MA (1)	-0.669	0.000	Significant
ARIMA (3,1,0)	AR (1)	-0.560	0.000	Significant
	AR (2)	-0.366	0.000	Significant
	AR (3)	-0.155	0.000	Significant
ARIMA (3,1,1)	AR (1)	0.364	0.000	Significant
	AR (2)	0.132	0.004	Significant
	AR (3)	0.165	0.000	Significant
	MA (1)	-0.980	0.000	Significant

From all the models that were successfully identified, the models that meet the significance criteria and will proceed to the diagnostic testing phase are ARIMA (0,1,1), ARIMA (3,1,0), and ARIMA (3,1,1). Two tests are then performed during the diagnostic testing phase: the Kolmogorov-Smirnov test for residual normality and the Ljung-Box test for residual independence. The results of these tests are presented in Table 5 below.

Table 5. Diagnostic Test Results

Variable	Ljung-Box *p-value*	Kolmogorov Smirnov *p-value*	Diagnostic Test Decision
ARIMA (0,1,1)	0.536	0.907	Meets both assumptions
ARIMA (3,1,0)	0.002	0.706	Does not meet both assumptions
ARIMA (3,1,1)	0.056	0.654	Meets both assumptions

Based on the results presented in Table 5, the models that successfully passed the diagnostic testing phase are ARIMA (0,1,1) and ARIMA (3,1,1). After passing the diagnostic tests, both models are further evaluated to determine the best model. Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) metrics are used to pick the model. The calculation results for MAPE, MAE, and RMSE for both models are presented in Table 6 below.

Table 6. Forecasting Accuracy of the ARIMA Input Model

Models	*MAPE*	*MAE*	RMSE
ARIMA (0,1,1)	0.841	0.069	0.088
ARIMA (3,1,1)	0.819	0.067	0.087

The ARIMA (3,1,1) model is the best model according to Table 6 as its MAPE, MAE, and RMSE values are lower than those of the other models. As a result, ARIMA (3,1,1) is determined to be the best model for predicting. The ARIMA (3,1,1) model is expressed as:

$$x_t - x_{t-1} - \phi_1 B x_t + \phi_1 B^2 x_t - \phi_2 B^2 x + \phi_2 B^3 x_t - \phi_3 B^3 x_t + \phi_3 B^4 x_t = a_t - \theta_1 B a_t$$

To find X_t, the ARIMA model becomes

$$x_t = (1+\phi_1)x_{t-1} - (\phi_1 - \phi_2)x_{t-2} - (\phi_2 - \phi_3)x_{t-3} - \phi_3 x_{t-4} + a_t - \theta_1 a_{t-1}$$

After substituting the estimated parameters from Table 4 and simplifying them, the model can be expressed as follows:

$$x_t = 1{,}364x_{t-1} - 0{,}232x_{t-2} + 0{,}033x_{t-3} - 0{,}165x_{t-4} + a_t + 0{,}980a_{t-1}$$

3.3. Prewhitening of Input and Output Series

Prewhitening is divided into two stages: prewhitening for the input series and prewhitening for the output series. The prewhitening equation for the input series, according to equation (1), is:

$$\alpha_t = \frac{(1 - 0.364B - 0.132B^2 - 0.165B^3)(1-B)}{(1+0.980B)} X_t$$

The prewhitening equation for the output series, according to equation (2), is:

$$\beta_t = \frac{(1 - 0.364B - 0.132B^2 - 0.165B^3)(1-B)}{(1+0.980B)} Y_t$$

3.4. Determination of the orders r, s, b

Finding the orders r, s, and b comes next when the prewhitening procedure is finished. The cross-correlation diagram between the series α_t and β_t is shown in Figure 2.

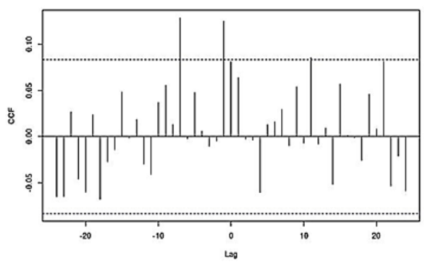


Figure 2. CCF Plot of $\boldsymbol{\beta_t}$ and $\boldsymbol{\alpha_t}$

Based on Figure 2, the orders r, s, and b are set as (2,0,0).

3.5. Single Input Transfer Function Model

The transfer function model formed according to equation (3) can be represented as follows:

$$y_t = \frac{\omega_0}{1 - \delta_1 B - \delta_2 B^2} x_t + a_t$$

Estimating the parameters in the transfer function model is the next stage. Table 7 below displays the findings of the parameter estimate for the transfer function model.

Table 7. Transfer Function Model Parameter Estimation

Parameter	Estimation
δ_1	0.875
δ_2	0.105
ω_0	0.000000087

Thus, the transfer function model becomes:

$$y_t = \frac{0.000000087}{1 - 0.875B - 0.105B^2} x_t + a_t$$

3.6. Diagnostic Tests

After parameter estimation is complete, the obtained model must go through a diagnostic testing phase. One important assumption in the transfer function model is that the residuals must be free from autocorrelation. To prove this, the ACF plot of the transfer function model residuals is evaluated.

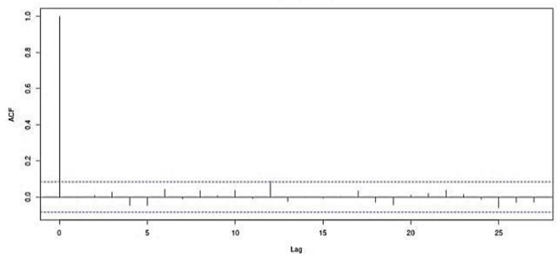


Figure 3. ACF Plot of Residuals from the Transfer Function Model

The assumption that the residuals of the transfer function model are autocorrelation-free has been met, as shown in Figure 3. Furthermore, Figure 4 presents the findings of the cross-correlation test.

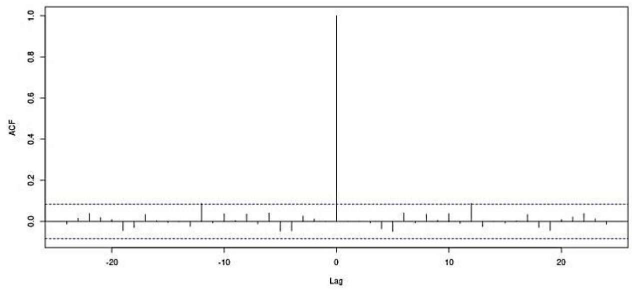


Figure 4. CCF Plot of $\boldsymbol{\alpha_t}$ and $\boldsymbol{a_t}$

As shown in Figure 4, the cross-correlation between the series α_t and a_t remains within the statistical significance bounds, indicating a lack of significant correlation. This result implies that the prewhitening process has been effective, and the residuals from the input and output series are no longer significantly correlated.

3.7. Forecasting

Using the established transfer function model, a forecast is made for the daily stock closing prices for the next five periods, from October 10 to October 14, 2024. Before making the forecast, a comparison is made between the model estimation and the actual values to assess the accuracy of the model. The comparison between the model's estimated results and the actual values can be seen in Figure 5.

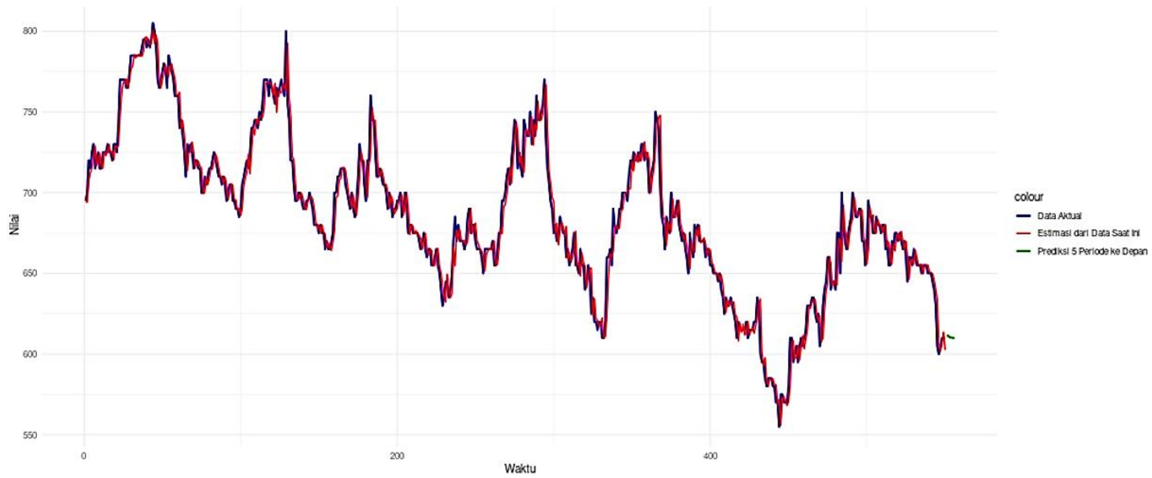


Figure 5. Comparison of Actual Data and Estimated Forecast

The predicted values exhibit a similar pattern to the real data utilized in the creation of the transfer function model, as seen by the comparison of the actual data with the forecast results in Figure 5. This study's assessment of predicting accuracy shows that the model works effectively. Based on the stock trading volume variable for the upcoming five periods, the resulting MAPE value of 1.09% supports this and indicates that the transfer function model is successful in forecasting the daily closing prices of PT. Dayamitra Telekomunikasi Tbk's stock.

After evaluating the forecasting model's accuracy, the next step is to forecast the stock closing prices using the established model. The results of the daily stock price forecast using the single input transfer function model are presented in Table 8 below.

Table 8. Stock Closing Price Forecast Results

Period	Prediction
October 10	611.434
October 11	611.348
October 12	610.272
October 13	610.316
October 14	610.069

Table 8 shows that the values obtained from the transfer function model forecast reflect a continuous fall, suggesting that the stock price of PT. Dayamitra Telekomunikasi Tbk will continue to deteriorate over the following five periods.

4. Conclusions

The transfer function is a model that not only considers the historical values of the output variable but also incorporates the influence of external variables that may affect the forecasting results. In the study of forecasting the daily stock closing price of PT. Dayamitra Telekomunikasi, a single-input transfer function model was used, where the stock closing price served as the output variable, and the stock trading volume was used as the input variable. The results of this study indicate that:

1. The transfer function model obtained has an order of (2,0,0) and is expressed in the following equation:

$$y_t = \frac{0.000000087}{1 - 0.875B - 0.105B^2} x_t + a_t$$

2. Based on the MAPE value for the next five periods, the model's forecasting accuracy is 1.09%, indicating a good level of accuracy.
3. The forecasting results for the next five periods yield the following values: 611.434; 611.348; 610.272; 610.316; and 610.069.

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