

Implementation of Transfer Function ARIMA Model for Stock Price Prediction

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ABSTRACT

Dynamic economic growth requires stable financing sources, one of which is through the capital market. In stock investment activities, risk and return are two fundamental aspects that are interrelated and must be carefully considered. The volatility of ASII stock prices, influenced by various factors including exchange rates, can create uncertainty in investment decision-making. This study aims to predict the stock price of PT Astra International Tbk (ASII) using a transfer function model approach that integrates the influence of the Indonesian rupiah to US dollar exchange rate as an external variable. The transfer function model is an extension of the ARIMA model that can measure the dynamic relationship between input and output variables. Based on the estimation results, the best model obtained has a transfer function order of $(b,s,r) = (1,0,0)$ with a noise series of $(p_n, q_n) = (1,0)$. The prediction results show that ASII stock price movements tend to be stable with a gradual decline over the next 20 days. Model evaluation demonstrates low error rates, with MAE of 84.19, RMSE of 110.37, and MAPE of 1.65%. These results indicate that the transfer function model is effective in modeling and predicting short-term stock prices with reasonably good accuracy.

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1. INTRODUCTION

Dynamic economic growth requires stable financing sources, one of which is through the issuance of stocks and bonds in the capital market [1]. The capital market plays a crucial role in providing funds for companies while creating investment opportunities for the public [2]. In making investment decisions, investors must consider two main aspects: *risk* and *return*, as both have an interconnected relationship [3]. Stock returns are significantly influenced by price volatility, which reflects the level of uncertainty in stock price movements due to various factors, including exchange rates [4].

Exchange rates play a significant role in determining a company's financial performance, particularly for firms engaged in export-import activities [5]. Exchange rate movements can directly affect operational costs, export revenues, and foreign debt burdens. A depreciation of the domestic currency (rupiah) against foreign currencies, such as the US dollar, can increase the cost of imported raw materials and foreign-denominated liabilities, thereby negatively impacting

profitability [6]. Conversely, it may benefit export-oriented firms by increasing the value of foreign earnings when converted into rupiah. Therefore, exchange rate volatility often introduces substantial uncertainty to the stock prices of affected companies, frequently resulting in a negative correlation between exchange rate depreciation and stock price performance.

PT Astra International Tbk was selected as the focus of this study due to its position as one of Indonesia's largest conglomerate companies with diversified business spanning automotive, heavy equipment, agribusiness, infrastructure, and technology [7]. As a company heavily engaged in international trade and foreign transactions, Astra's financial performance is particularly sensitive to exchange rate fluctuations. While the company's stock price has generally exhibited an upward trend over the long term, it remains vulnerable to market volatility and macroeconomic shocks, including exchange rate pressures [8].

According to data from the Indonesia Stock Exchange, PT Astra International Tbk (ASII) shares experienced a significant decline with the lowest price reaching Rp 4.950 on April 19, 2024. This decline was triggered by increased investor selling activity and unfavorable market sentiment. In addition to internal factors and sentiment, fluctuations in the Indonesian rupiah against the US dollar also exerted pressure on ASII's performance, particularly during the period from 2021 to 2022. In 2021, the rupiah exchange rate weakened to Rp 14.569 per US dollar, and in 2022 experienced further depreciation of 9.31% to Rp 15.731 due to tighter monetary policy from the United States [9]. This depreciation was largely influenced by the tightening of United States monetary policy, which triggered capital outflows from emerging markets such as Indonesia.

These conditions have created significant uncertainty for long-term investors, particularly those who rely on price stability to formulate their investment strategies. In order to address market volatility and the risks associated with exchange rate fluctuations, a more comprehensive risk management approach is needed, one that incorporates quantitative methods [10]. One such approach is the time series method, which is a systematic process used to predict the most likely future events based on currently available data and information, such as the application of transfer function models [11].

The transfer function model is one of the approaches in time series analysis used to measure the dynamic relationship between one input variable (*independent*) and an output variable (*dependent*) over time [12]. This model is an extension of the ARIMA model that allows the integration of external variables [13]. ARIMA itself is a method commonly used in time series analysis because it is effective in identifying patterns from historical data and predicting stock price movements [14]. By combining regression analysis and ARIMA, the transfer function model can produce more accurate estimates of the relationship between independent and dependent variables.

Several previous studies have shown that the transfer function model offers higher accuracy compared to other models. For instance, research conducted by S. P. Prahesti et al. using ARIMA and transfer function methods on coal reference price data showed that the transfer function model provided more accurate results, with a Mean Absolute Percentage Error (MAPE) of 17.66%, which was lower than the ARIMA model's MAPE of 23.14% [15]. Additionally, research by N. Rahmawati et al. comparing transfer function and Neural Network models in predicting BBKA stock closing prices also demonstrated that the transfer function model was the superior model, with a MAPE of 0.17764, which was significantly lower than the Neural Network's MAPE of 0.38200 [16].

Based on the results of previous research demonstrating the superiority of the transfer function model in producing accurate predictions, this study aims to apply and test the effectiveness of the model in predicting PT Astra International Tbk (ASII) stock prices, by incorporating fluctuations in the Indonesian rupiah against the US dollar exchange rate as an external variable. The main objective of this research is to prove whether the transfer function model can provide more accurate and stable prediction results compared to other commonly used models, such as ARIMA. Through this approach, it is expected that the research can contribute to the development of more targeted investment strategies and expand understanding of the dynamic relationship between external factors, particularly exchange rates, and corporate stock performance.

2. RESEARCH METHOD

This study follows a systematic sequence of steps to develop a forecasting model using the Transfer Function approach integrated with ARIMA modeling. The methodology comprises several stages, as shown in Figure 1.

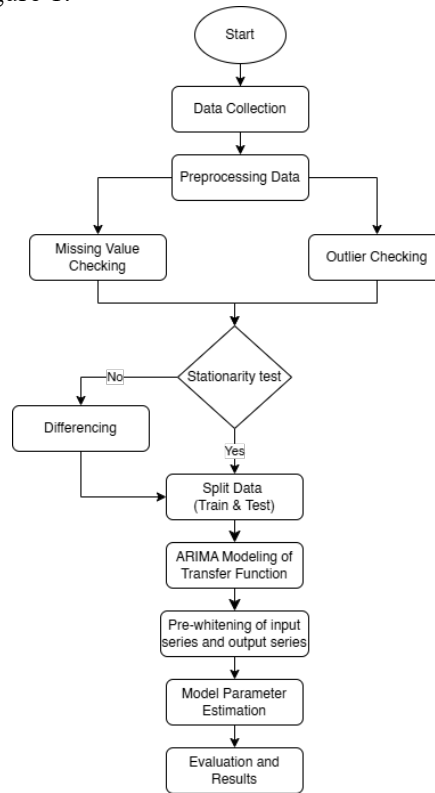


Figure 1. Research Flowchart

2.1. AutoRegressive Integrated Moving Average (ARIMA)

The ARIMA method is one of the time series forecasting methods that combines *autoregressive* (AR) and *moving average* (MA) components to model non-stationary time series data. To address non-stationarity, a *differencing* process is performed to eliminate trends or seasonal patterns, making the data stationary [17]. Generally, the ARIMA model is represented in the form ARIMA(p , d , q), where p indicates the autoregressive order, d represents the number of differencing required to make the data stationary, and q is the moving average order [18]. The ARIMA model equation can be expressed as follows:

$$\phi_p(B)(1-B)^d Z_t = \theta_0 + \theta_q(B)a_t \quad (1)$$

where $\phi_p(B) = (1 - \phi_1 B - \dots - \phi_p B^p)$ represents the *autoregressive* (AR) parameters, which are required to be stationary, and $\theta_q(B) = (1 - \theta_1 B - \dots - \theta_q B^q)$ represents the *moving average* (MA) parameters, which must be invertible.

The ARIMA model development process begins by ensuring that the data satisfies the stationarity assumptions for both variance and mean. When the data exhibits non-stationary variance, the Box-Cox transformation can be employed as a remedial measure. Meanwhile, if non-stationarity occurs in the mean values, differencing techniques are applied to eliminate trends or seasonal patterns [19].

2.2. Transfer Function

The transfer function model is an approach in time series analysis used to evaluate the relationship between two variables, namely *input* and *output* [20]. Its primary objective is to construct a quantitative model that can predict future output values based on historical data from

both input and output variables, while accounting for the effects of disturbance factors [21]. Mathematically, a transfer function model with a single input and single output can be expressed as follows.

$$y_t = v(B)x_t + \eta_t \quad (2)$$

description:

y_t = value of the *output* variable at time t

x_t = value of the *input* variable at time t

η_t = *noise*

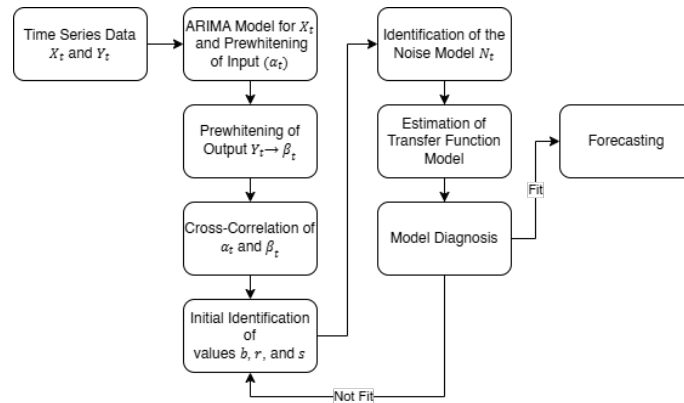


Figure 2. Transfer function modeling steps

The development of the transfer function model is conducted systematically to obtain a precise and accurate representation of the relationship between the input and output variables. As shown in Figure 2, the model development process consists of the following stages:

- Preparing the input series (x_t) of exchange rate values and the output series of ASII stock prices (y_t) that have undergone preprocessing.
- ARIMA modeling and *pre-whitening* of the input series (x_t) to eliminate autocorrelation, resulting in a white noise series (α_t).
- Pre-whitening* of the output series (y_t) to eliminate autocorrelation, thereby obtaining a white noise series (β_t).
- Calculating the *Cross-Correlation Function* (CCF) between the pre-whitened input and output series.
- Determining the order of the transfer function model (b,r,s)
- Initial estimation of the noise series (n_t)
- Establishing the Order (p_n, q_n) for the ARIMA Model on the noise series (n_t)
- Parameter estimation of the Transfer Function Model.
- Forecasting ASII stock prices for the next 20 days and calculating the accuracy of the predictions.

2.3. Forecasting

Forecasting is a method for predicting future values based on historical and current data [22]. This process plays a crucial role in decision-making, as many determining factors are not visible when decisions are made. In time series models, forecasting is performed by calculating the conditional expectation directly from the difference equation of the process [23].

2.4. Data

This study uses daily closing price data of PT Astra International Tbk (ASII) stocks obtained from the Investing.com platform, as well as exchange rate data sourced from Bank Indonesia. The data covers the period from September 2019 to September 2024, with a total of 1213 data points analyzed. Both datasets are publicly accessible and can be downloaded from the official websites of Investing.com (<https://www.investing.com>) and Bank Indonesia

(<https://www.bi.go.id>), ensuring transparency and reproducibility of the research. The variables used in this study are presented in Table 1.

Table 1. Research Variables

Variable	Information	Data Type
Date	Stock transaction dates occur within a certain time range	<i>Datetime</i>
Close ASII (Y)	The closing price of shares (close price) at the end of the trading day	<i>Float</i>
Kurs USD (X_t)	USD exchange rate	<i>Float</i>

- PT Astra International Tbk

PT Astra International Tbk is one of the largest conglomerates in Indonesia that operates its business across various industrial sectors, particularly in automotive, heavy equipment, agribusiness, infrastructure, and financial services [24].

- Exchange Rate (*Kurs*)

The exchange rate represents the amount of one country's currency required to obtain one unit of another country's currency. Exchange rate determination is established through market dynamics based on the equilibrium between foreign exchange demand and supply[25].

The exchange rate is used as an external variable because ASII operates in sectors sensitive to currency fluctuations, such as automotive and agriculture. A weaker Rupiah can increase import costs and reduce profit margins, which may impact stock prices. Therefore, including the exchange rate helps improve the accuracy of ASII stock price prediction.

2.5. Model Evaluation

The evaluation of the predictive models in this study was conducted using a train-test split approach with a ratio of 80:20. A total of 966 data points were used for training, while 242 data points were allocated for testing the model's performance.

- Akaike Information Criterion (AIC)

This criterion is used to evaluate the residuals, where a smaller AIC value indicates a better-fitting model [26]. The AIC value can be calculated using the following formula:

$$AIC(M) = n \ln \hat{\sigma}_a^2 + 2M \quad (3)$$

description:

n : number of residuals
 M : number of model parameters
 $\hat{\sigma}_a^2$: estimator of σ_a^2

- Root Mean Square Error (RMSE)

RMSE is one of the most commonly used evaluation methods in predictive research, as it quantitatively measures the average error between predicted values and actual values [27]. The following is the formula for RMSE:

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n (y_t - \hat{y}_t)^2} \quad (4)$$

- Mean Absolute Error (MAE)

MAE is an evaluation method used to measure the average absolute error between predicted and actual values, providing an indication of the median magnitude of error in the predictive model [28].

$$MAE = \frac{1}{n} \sum_{t=1}^n |y_t - \hat{y}_t| \quad (5)$$

- *Mean Absolute Percentage Error (MAPE)*

MAPE is used to measure the performance of forecasting models. The smaller the MAPE value and the closer it is to the actual value, the better the model performance is considered [29]. The criteria for evaluating MAPE values are presented in Table 2. The MAPE value is calculated using the following formula:

$$MAPE = \frac{1}{n} \sum_{t=1}^n \left| \frac{y_t - \hat{y}_t}{y_t} \right| \times 100\% \quad (6)$$

description:

y_t : actual value at time t
 $\hat{y}_t$: forecasted value at time t
 n : number of data points

Table 2. MAPE Evaluation Criteria

MAPE Value (%)	Criteria
< 10%	Highly Accurate Forecast
10% – 20%	Good Forecast
20% – 50%	Reasonable Forecast
> 50%	Inaccurate Forecast

3. RESULTS AND DISCUSSION

The prediction process in this study begins with the preprocessing of two types of data: the daily closing stock prices of PT Astra International Tbk (ASII) and the exchange rate (USD to IDR). These datasets are presented in Table 3.

Table 3. ASII Stock Price and Exchange Rate Data

Date	ASII Close	Kurs
2019-09-20	6575	14155.0
2019-09-23	6625	14147.0
2019-09-24	6475	14169.0
...	...	...
2024-09-18	5250	15414.69
2024-09-19	5275	15426.75
2024-09-20	5225	15363.43

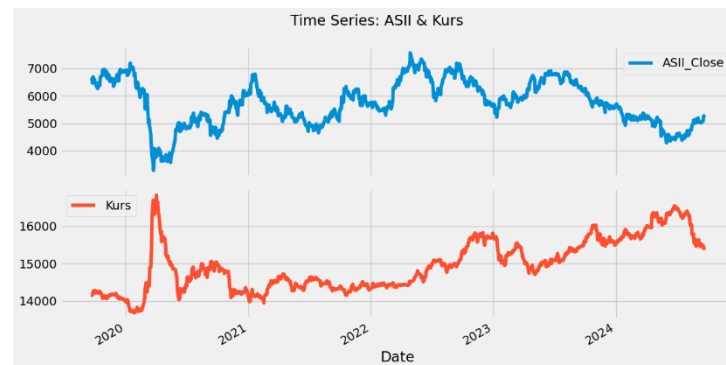


Figure 3. Data Plot of ASII Stock and Exchange Rate

Based on Figure 3, it can be observed that both datasets exhibit fluctuating trends over time. The ASII stock price demonstrates a generally downward trend, reaching its highest value of

6,300 on September 20, 2023, and its lowest value of 4,290 on May 31, 2024. In contrast, the USD to Rupiah exchange rate shows noticeable volatility, with the highest recorded value of 16,540.29 on June 24, 2024, and the lowest value of 15,363.43 on September 20, 2024.

Both data plots demonstrate non-stationary patterns, evident from the presence of trends and variability that change over time. Before conducting further testing, the data were first examined to ensure there were no missing values or outliers. The examination results showed that there were no missing values or outliers in both datasets, so the data could be used directly for stationarity analysis.

Table 4. Stationarity Test before Differencing

Variable	ADF test	P-value
ASII_Close (Y)	-2.483045183780151	0.11965430257597554
Kurs(X_t)	-2.6437290743140367	0.08429188705748869

The stationarity test was conducted using the *Augmented Dickey-Fuller* (ADF) method. The test results in Table 4 showed that ASII stock price data had an ADF Statistic of -2.4830 with a p-value of 0.1196, while USD to rupiah exchange rate data had an ADF Statistic of -2.6437 with a p-value of 0.0842. Since the p-values for both datasets were greater than the significance level of 0.05, the test decision was to fail to reject the null hypothesis, meaning both datasets are non-stationary at the level.

Table 5. Stationarity Test after Differencing

Variable	ADF test	P-value
ASII_Close (Y)	-37.191746602415066	0.0
Kurs(X_t)	-8.758530835704965	2.713613429901319e-14

To address this non-stationarity, a transformation was performed using the *first differencing* method. After differencing, the ADF test results in Table 5 showed that ASII stock price data had an ADF Statistic of -37.1917 with a p-value 0.0, while the USD exchange rate data showed an ADF Statistic of -8.7585 with a p-value of 2.71×10^{-14} . With p-values significantly smaller than 0.05, the test decision was to reject H_0 , indicating that both datasets had become stationary after differencing.

The next stage involved forming an ARIMA model with parameters (p,d,q), where d=1, based on the previous first differencing transformation results. ARIMA modeling requires fulfillment of the assumption that model residuals must exhibit white noise properties and be normally distributed.

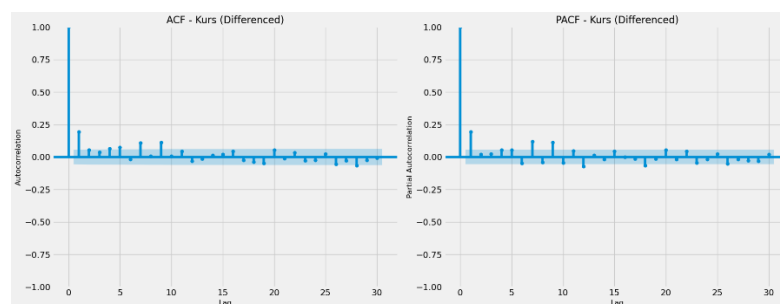


Figure 4. ACF & PACF Plot of Kurs

Based on Figure 4, the ACF plot showed significant autocorrelation at lag 1, while subsequent lags remained within the significance bounds, indicating a rapid decline in autocorrelation. Similarly, the PACF plot exhibited a prominent spike at lag 1 followed by a sharp drop, suggesting limited partial autocorrelation beyond the first lag. This pattern indicates that

appropriate candidate models include ARIMA(1,1,0), ARIMA(0,1,1), ARIMA(1,1,1), ARIMA(2,1,0), ARIMA(0,1,2), and ARIMA(2,1,2). To determine the best-fitting model, each candidate was estimated and compared using the *Akaike Information Criterion* (AIC), with the model yielding the lowest AIC selected as the most suitable for forecasting.

Table 6. ARIMA Model Candidate Selection

Model	Parameter	AIC
ARIMA(1,1,0)	$\phi_1 = -0.413583$ $\sigma^2 = 5571.91$	13885.46
ARIMA(0,1,1)	$\theta_1 = -0.921648$ $\sigma^2 = 4183.22$	13540.80
ARIMA(1,1,1)	$\phi_1 = 0.195402$ $\theta_1 = -0.999842$ $\sigma^2 = 4014.27$	13497.70
ARIMA(2,1,0)	$\phi_1 = -0.536588$ $\phi_2 = -0.297422$ $\sigma^2 = 5081.68$	13775.24
ARIMA(0,1,2)	$\theta_1 = -0.815925$ $\theta_2 = -0.183795$ $\sigma^2 = 4025.04$	13500.72
ARIMA(2,1,2)	$\phi_1 = -0.725273$ $\phi_2 = 0.140618$ $\theta_1 = -0.058771$ $\theta_2 = -0.941142$ $\sigma^2 = 3959.62$	13485.57

Among the candidate models in Table 6, ARIMA(2,1,2) was selected as the best model based on the lowest AIC value, indicating the optimal balance between model complexity and data fit. Diagnostic analysis showed that the residuals behaved as white noise, with no significant autocorrelation and a random distribution. Therefore, this model was deemed suitable for the prewhitening process. The general form of the ARIMA(2,1,2) model is expressed as follows:

$$(1 - B)X_t = (1 + \theta_1 B)\epsilon_t$$

where B is the backward shift operator, θ_1 is the *moving average* (MA) parameter, and ϵ_t represents *white noise*.

Based on the estimation results from the ARIMA(2,1,2) model applied to the input series (exchange rate), the *autoregressive parameters* ϕ_1 and ϕ_2 were estimated as -0.725273 and 0.140618, respectively. The *moving average parameters* θ_1 and θ_2 were estimated as -0.058771 and -0.941142, respectively. These estimates were obtained through model fitting using statistical software, where each coefficient reflects the strength and direction of lagged dependencies in the data. In particular, the coefficient of the second-order MA term (θ_2) was found to be -0.941142, indicating a strong inverse correlation at lag 2 in the error term. To facilitate the prewhitening process, the white noise component α_t was isolated by transforming the input series (X_t) as follows:

$$\alpha_t = \frac{(1 + 0.058771B + 0.941142B^2)}{(1 + 0.725273B - 0.140618B^2)} X_t \quad (5)$$

This transformation removes the autocorrelation from the input series, resulting in a prewhitened input. Subsequently, the same filter was applied to the output series to ensure comparability in the cross-correlation analysis. The transformed output series β_t was defined as:

$$\beta_t = \frac{(1 + 0.058771B + 0.941142B^2)}{(1 + 0.725273B - 0.140618B^2)} Y_t \quad (6)$$

After the prewhitening process was performed on both series, the analysis continued with calculating the *cross-correlation function* (CCF) between the input series residuals and output series residuals, with results shown in Figure 5 below.

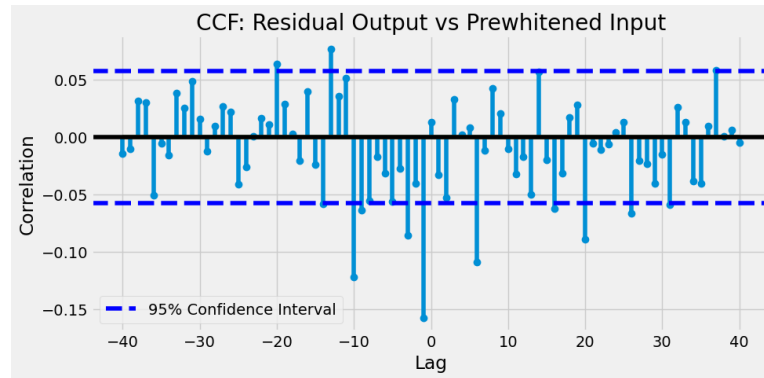


Figure 5. Cross-correlation Plot Between α_t & β_t

Based on Figure 5, there is evidence of significant correlation between the prewhitened input and residual output at lag 0 ($b = 0$), as indicated by the correlation value exceeding the 95% confidence interval boundaries at this lag. Since the most significant correlation occurs at lag 0 and no other substantial correlation patterns were observed at subsequent lags, the values $b = 0$, $s = 0$, and $r = 1$ were selected as initial parameter estimates for the transfer function model. Subsequently, residual examination was conducted by analyzing the ACF and PACF plots of the model residuals to determine the noise series order (p_n, q_n) . Based on this analysis, the most appropriate noise series order is $(p_n, q_n) = (1, 0)$.

The selection of the optimal transfer function model was based on the lowest *Akaike Information Criterion* (AIC) value and parameter significance within the model. According to these criteria, the best transfer function model is the model with order $(b, s, r) = (1, 0, 0)$ and noise series $(p_n, q_n) = (1, 0)$. The resulting model can be expressed in the following difference equation form:

$$y_t = \frac{\omega(B)}{\delta(B)} x_{t-b} + \frac{\theta(B)}{\phi(B)} a_t \quad (7)$$

Based on the model estimation results, the following coefficient values were obtained:

- The coefficient for the input variable (*exchange rate*), ω is -0.206017 .
- The *autoregressive* (AR) coefficient of the output series, ϕ is -0.092836 .
- There is no *moving average* (MA) term estimated, as the noise model is AR(1) based on previous analysis.

To express the model in the standard difference equation, the AR coefficient is written as a positive value on the left-hand side of the equation, resulting in:

$$y_t = \frac{-0.206017}{1 + 0.092836B} x_t + a_t \quad (8)$$

in the form of a full difference equation:

$$y_t = -0.206017 x_t - 0.092836 y_{t-1} + a_t \quad (9)$$

This model indicates that the current value of the output series (y_t , ASII stock price) is influenced contemporaneously by the input series (x_t , exchange rate) and the lagged value of the output itself (y_{t-1}), along with the error term at time t . The absence of significant MA terms in the residuals suggests that the noise series follows a simple AR(1) structure. After obtaining the best transfer function model, the next step involves conducting forecasts for the subsequent 20 days. The prediction results for ASII stock prices using the developed transfer function model are presented as follows, as shown in Table 7.

Table 7. ASII Stock Price Prediction Results (Next 20 Days):

Date	Price Prediction (Rp)
2024-09-23	5,205.39
2024-09-24	5,210.02

2024-09-25	5,246.10
2024-09-26	5,219.38
2024-09-27	5,226.21
2024-09-30	5,240.09
2024-10-01	5,226.84
2024-10-02	5,213.79
2024-10-03	5,209.44
2024-10-04	5,223.32
2024-10-07	5,239.88
2024-10-08	5,247.75
2024-10-09	5,232.43
2024-10-10	5,232.22
2024-10-11	5,238.84
2024-10-14	5,237.60
2024-10-15	5,240.92
2024-10-16	5,254.79
2024-10-17	5,252.30
2024-10-18	5,265.35

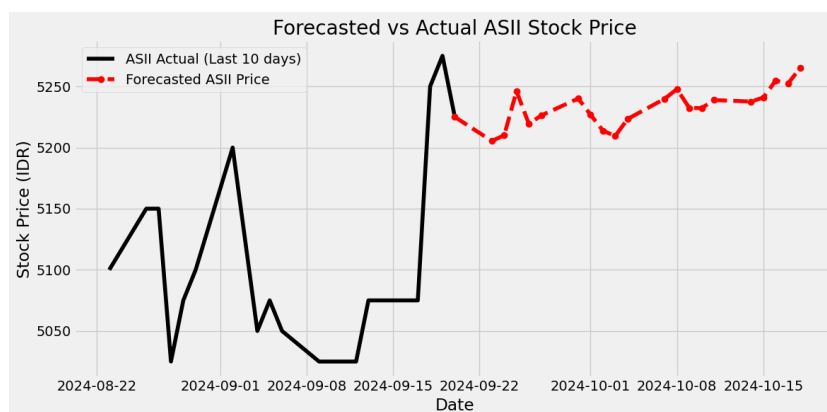


Figure 6. Plot of Actual Data vs Predicted ASII Stock Price

The prediction results shown in Figure 6 indicate that the ASII stock price is expected to remain relatively stable over the forecast horizon from September 23 to October 18, 2024. The predicted stock prices range from Rp 5,205.39 to Rp 5,265.35, reflecting a mild upward trend toward the end of the prediction period. Overall, the stock price is projected to increase by approximately Rp 59.96 or around 1.15%, indicating a modest but steady rise in value. Daily fluctuations are relatively small, generally within the range of Rp 10–25, suggesting low short-term volatility and consistent price behavior. The transfer function model was then compared with the standard ARIMA model for forecasting ASII stock prices. The dataset was split into training and testing sets with an 80:20 ratio. The prediction accuracy of both models was evaluated using performance metrics, with the results summarized as shown in Table 8.

Table 8. Accuracy of ARIMA Model & Transfer Function Model

Accuracy	ARIMA	Transfer Function
MAE	1078.66	84.19
RMSE	1193.56	110.37
MAPE	21.83%	1.65%

While this study employs a single 80:20 train-test split for model evaluation, this approach is considered sufficient given the context and purpose of the analysis. The resulting performance metrics clearly demonstrate the robustness of the transfer function ARIMA model. Based on table 8, the transfer function model outperforms the standard ARIMA model in forecasting ASII stock prices. The transfer function model achieved a significantly lower MAE of 84.19 and RMSE of 110.37, indicating that its predictions are much closer to the actual values. Additionally, the MAPE value of 1.65% suggests a low average percentage error, reflecting high prediction accuracy and strong performance for short-term forecasts. These results confirm that even without the use of cross-validation or walk-forward testing, the chosen evaluation method provides reliable and valid insights into model performance.

4. CONCLUSION

Based on the analysis conducted, it can be concluded that the optimal model identified in this study is the transfer function model with orders $(b, s, r) = (1, 0, 0)$ and noise series orders $(p_n, q_n) = (1, 0)$. The model successfully predicts ASII stock prices with a stable trend and low short-term volatility during the forecast period from September 23 to October 18, 2024, with predicted prices ranging from Rp 5,205.39 to Rp 5,265.35. Compared to the standard ARIMA model, the transfer function model provides more accurate forecasts, as reflected by lower MAE (84.19), RMSE (110.37), and MAPE (1.65%). These results confirm the model's strong performance for short-term stock price prediction.

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