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Prediction of Weekly Stock Price of PT Indofood CBP Sukses Makmur Tbk (ICBP) with ARIMA Box-Jenkins Method

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Abstract— This research aims to forecast the weekly stock prices of PT Indofood CBP Sukses Makmur Tbk (ICBP) using the ARIMA model based on the Box-Jenkins methodology. Weekly closing price data from January 1 2024 to January 26 2025 is utilized as the basis for analysis. The data is first tested for stationarity, and appropriate differencing is applied to stabilize the mean. The ARIMA(2,1,0) model is identified as the best-fitting model. Model diagnostics, including the Ljung-Box test, confirm that the residuals exhibit white noise characteristics, indicating a good model fit. Forecasting performance is assessed using the Mean Absolute Percentage Error (MAPE), which resulted in a value of 1.58%, suggesting a high level of forecasting accuracy. The findings demonstrate that the ARIMA model is effective for short-term stock price prediction and can serve as a useful tool for investors and financial analysts.

Keywords— Time Series; ARIMA; Forecasting; Stock Price

I. INTRODUCTION

Stock market forecasting plays an important role in guiding investors, analyzing finances, and also helping corporate managers make data-driven decisions. If stock market predictions are accurate, it can help optimize investment strategies, minimize financial risks, and match corporate planning with market dynamics. One of the leading consumer goods companies in Indonesia, PT Indofood CBP Sukses Makmur Tbk (ICBP), has significant stock performance to influence the investment portfolios of individual and institutional investors. Because the strategy is important, it is important to develop a reliable, practical and academically valuable model to estimate ICBP stock prices.

Predicting stock prices is challenging because financial time series data tends to be non-linear, dynamic, and often quite volatile. Even though a lot of new machine learning and statistical techniques are being developed, traditional time series methods like the Box-Jenkins ARIMA model are still considered reliable and widely used — especially when working with univariate data that depends on time [1]. ARIMA offers a structured way to analyze and forecast data by looking at patterns in autocorrelation and making sure the data is stationary before building a model.

The ARIMA model has been applied in previous studies to forecast stock prices in various companies. For example, Laskarjati and Ahmad (2022) compared the ARIMA model with the Fuzzy Time Series Markov Chain method in predicting the stock price of PT Indofood CBP Sukses Makmur Tbk [2]. From these results, the use of the Fuzzy Time Series Markov Chain method provides slightly better accuracy in certain scenarios, although both methods are effective. Similar to Dewanti et al. (2024) who used a hybrid model by combining Singular Spectrum Analysis (SSA) and ARIMA to predict the stock price of PT Indofood Sukses Makmur Tbk, this study has shown an increase in forecasting performance [3].

Although various methods continue to develop, there is still a gap in research that specifically applies the ARIMA Box-Jenkins method to ICBP's weekly stock price data [1]. Most previous studies have used more daily or monthly data, even though there may be patterns or trends that are more clearly visible when viewed weekly. In addition, the unique market conditions and various events that affect the movement of ICBP's stock price also require adjustments to the model used in order to capture the dynamics of its stock price movements more accurately.

Therefore, the purpose of this study is to build a reliable and easy-to-understand time series model to predict ICBP weekly stock prices with high accuracy. It is expected that the results of this study can help investors in making more informed decisions, as well as being a tool for companies to plan finances and respond better to market changes.

II. METHODOLOGY

In this study, the forecasting method used is the Box-Jenkins ARIMA model. One of the most extensively used and dependable time series forecasting methods in a variety of disciplines, including finance and economics, is ARIMA, or Autoregressive Integrated Moving Average. Introduced by Box and Jenkins in the 1970s, this method offers a systematic approach consisting of several stages, starting from model identification, parameter estimation, diagnostic checking, and forecasting [1]. The ARIMA model works by capturing patterns and relationships in historical data and using them to predict future values, as long as the data is stationary. If the data is not stationary, it needs to be differentiated to stabilize the mean and remove trends or seasonality. Its ability to handle various types of time series data and provide clear, interpretable models makes the ARIMA method one of the go-to tools in time series analysis.

The ARIMA model combines three main components:

1. *Autoregressive (AR)*

The AR component uses the relationship between the current value and its previous values. It assumes that today's stock price is influenced by stock prices from the previous periods. The formula is:

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

Where:

Y_t : Value at time t

ϕ : Autoregressive coefficient

p : Order of the AR term

e_t : Error at time t

2. *Moving Average (MA)*

The MA component explains the current value based on the error terms from the previous periods. In other words, it accounts for the influence of previous forecast errors. The formula is:

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

Where:

θ : Moving average coefficient

q : Order of the MA term

3. *Autoregressive Integrated Moving Average (ARIMA)*

The Autoregressive (AR) model and Moving Average (MA) model equations can be combined and written as the ARMA model. The equation for the ARIMA (p,d,q) model is:

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

Then, to forecast non-stationary data, differencing is applied to transform the data into a stationary form, resulting in the ARIMA model by combining the AR and MA methods and using differencing $Wt = \nabla^d Yt$. The ARIMA equation can be written as:

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

Where:

Y_t : Value at time t

Y_{t-p} : Value at lag p

e_t : Error at time t

ϕ_p : Autoregressive coefficient at lag p

θ_q : Moving Average coefficient at lag q

W_t : Differencing process

In this forecasting project, several R packages are installed to support data manipulation, time series modeling, visualization, and evaluation. The following packages are essential components of the workflow: *install.packages("tidyr")*, *install.packages("readxl")*, *install.packages("forecast")*, *install.packages("tseries")*, *install.packages("ggplot2")*, *install.packages("lubridate")*, and *install.packages("Metrics")*.

1. tidyr

The `tidyr` package is used to clean and reshape data into a tidy format. It allows us to organize the dataset efficiently so that each variable forms a column, each observation forms a row, and each value has its own cell — which is crucial before performing time series analysis.

2. readxl

The `readxl` package enables the reading of Excel files (.xls, .xlsx) into R. In this project, it is used to import stock price data from Excel spreadsheets.

3. forecast

This is the core package for building and evaluating ARIMA models. It provides the Arima(), auto.arima(), and forecast() functions which are used to model and generate forecasts for the stock price data.

4. tseries

`tseries` supports time series analysis by providing statistical tests and additional tools, such as:

- ADF Test (adf.test()): to test stationarity

- And more functions for ARIMA-related diagnostics

5. ggplot2

This is a powerful visualization package based on the Grammar of Graphics. It is used to create customized and publication-ready plots, such as line charts for actual vs. forecasted stock prices and confidence intervals.

6. lubridate

`lubridate` simplifies working with date and time data. In time series forecasting, it helps generate sequences of weekly or monthly dates, parse date formats, and manipulate date values.

7. Metrics

The `Metrics` package provides functions to compute forecast accuracy metrics such as:

- MAE (Mean Absolute Error)

- RMSE (Root Mean Squared Error)

- MAPE (Mean Absolute Percentage Error)

These are used to evaluate the performance of the ARIMA model's predictions.

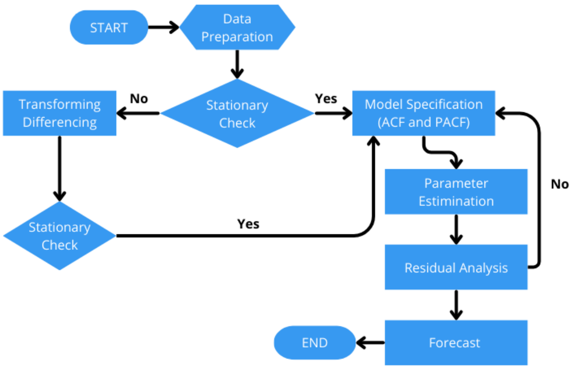

Figure. 1 ARIMA Forecasting Steps

The ARIMA forecasting process involves several structured steps to ensure accurate time series predictions. It begins with data preparation, where the data is cleaned and organized. Next is checking for stationarity—a requirement for ARIMA models—where non-stationary data is differenced until it becomes stationary. Once stationarity is confirmed, the model specification step involves selecting the appropriate ARIMA (p, d, q) parameters. Following that, parameter estimation is conducted to determine the best-fitting values for the chosen model. A diagnostics test then evaluates the residuals to ensure the model assumptions are met; if they are not, adjustments are needed. There are important statistical tools: Log-Likelihood and Akaike Information Criterion (AIC) for parameter estimation, and Shapiro-Wilk Test and Ljung-Box Test for residual analysis.

1. Log-Likelihood (in Parameter Estimation)

The log-likelihood function measures how well a statistical model explains the observed data. In the ARIMA model, the log-likelihood is used to estimate model parameters through Maximum Likelihood Estimation (MLE). A higher log-likelihood indicates a better model fit.
Formula:

$$log\ L\ =\ -\frac{n}{2}log(2\pi)-\frac{n}{2}log(\sigma^2)-\frac{1}{2\sigma^2}\sum_{t=1}^{n}e_t^2$$

Where:

- n : number of observations

- σ^2 : variance of residuals

- e_t : residuals (errors) from the model

2. Akaike Information Criterion (AIC)

AIC is a criterion for model selection that balances goodness-of-fit and model complexity. It penalizes models with more parameters to avoid overfitting.

Formula:

$$AIC\ =\ 2k\ -\ 2log(L)$$

Where:

- k : number of parameters

- log(L) : log-likelihood of the model

3. Shapiro-Wilk Test (Normality of Residuals)

The Shapiro-Wilk test assesses whether a sample comes from a normally distributed population. In time series, it is used to test whether residuals are normally distributed, which is an assumption for many statistical models.

The Shapiro-Wilk test statistic is defined as:

$$W\ =\ \frac{(\sum_{i=1}^{n}a_i\,x_{(i)})^2}{\sum_{i=1}^{n}(x_i-\bar{x})^2}$$

Where:

- x_i : the i-th order statistic (sorted sample value)

- $\bar{x}$: the sample mean

- a_i : constants calculated from the expected values and variances of order statistics from a standard normal distribution

- n : the number of observations

A value of W close to 1 indicates normality. A p-value greater than 0.05 suggests that the residuals are normally distributed.

4. Ljung-Box Test (Independence of Residuals)

The Ljung-Box test checks for autocorrelation in the residuals of a time series model. It's a diagnostic tool to ensure that the model has captured all temporal structure.

Formula:

$$Q = n(n+2)\sum_{k=1}^{h}\frac{\hat{r}_k^2}{n-k}$$

Where:

- r_k : autocorrelation at lag k

- n : sample size

- h : number of lags

A p-value greater than 0.05 means residuals are independently distributed.

Once the model passes all tests, it proceeds to the next step: forecasting, where future values are predicted based on the established model. After that, based on the forecast value, the most appropriate ARIMA model for forecasting can be identified by comparing the error values (MSE, RMSE, MAE, and MAPE) between models.

Forecast Accuracy Metrics and Their Formulas:

1. *Mean Squared Error (MSE)*

MSE measures the average of the squared differences between actual and predicted values. It penalizes larger errors more severely.

Formula:

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(yt - \hat{y}\,t)^2$$

2. *Root Mean Squared Error (RMSE)*

RMSE is the square root of MSE, bringing the error measurement back to the original scale of the data. It is widely used for its interpretability.

Formula:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(yt - \hat{y}\,t)^2}$$

3. *Mean Absolute Error (MAE)*

MAE measures the average of the absolute differences between actual and predicted values. It is less sensitive to outliers compared to MSE and RMSE.

Formula:

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|yt - \hat{y}\,t|$$

4. *Mean Absolute Percentage Error (MAPE)*

MAPE calculates the average absolute percentage difference between actual and predicted values, expressed as a percentage. It provides an intuitive interpretation but is undefined when actual values are zero.

Formula:

$$MAPE = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{yt - \hat{y}t}{yt}\right|$$

Where:

yt : Actual value at time

$\hat{y}t$: Predicted value at time

n : Number of data points

MAPE values can be interpreted into four categories, namely: < 10% = very accurate, 10 - 20% = good, 20 - 50% = reasonable, and > 50% = inaccurate [7].

The model that achieves the lowest error value compared to other models indicates that ARIMA is the most accurate model for forecasting stock prices in the given analysis.

III. RESULT AND DISCUSSION

A. Data Preparation

In this research, weekly stock price data for PT Indofood CBP Sukses Makmur Tbk (ICBP) from January 1, 2024, to January 26, 2025, amounting to 55 observations, is used. The data, sourced from Investing.com, is presented in Table 1 and Figure 1, and processed using R Studio. From the total dataset, 51 observations are used as training data, while the remaining 4 observations are used as test data for model evaluation.

TABLE 1
DATA OF THE STOCK PRICE OF PT INDOFOOD CBP SUKSES MAKMUR TBK (ICBP)

Date	Price	Date	Price	Date	Price
1/7/2024	11,175	5/12/2024	10,550	9/8/2024	11,325
1/14/2024	11,550	5/19/2024	10,475	9/15/2024	12,000
1/21/2024	11,450	5/26/2024	9,750	9/22/2024	12,650
1/28/2024	11,575	6/2/2024	10,575	9/29/2024	12,125
2/4/2024	11,425	6/9/2024	10,500	10/6/2024	12,250
2/11/2024	11,450	6/16/2024	10,300	10/13/2024	12,800
2/18/2024	11,550	6/23/2024	10,300	10/20/2024	12,650
2/25/2024	11,625	6/30/2024	10,275	10/27/2024	12,100
3/3/2024	10,775	7/7/2024	10,375	11/3/2024	12,100
3/10/2024	10,725	7/14/2024	10,800	11/10/2024	11,675
3/17/2024	11,125	7/21/2024	10,850	11/17/2024	12,000
3/24/2024	11,600	7/28/2024	11,175	11/24/2024	11,900
3/31/2024	10,850	8/4/2024	11,200	12/1/2024	11,825
4/14/2024	9,725	8/11/2024	11,375	12/8/2024	11,850
4/21/2024	10,600	8/18/2024	11,475	12/15/2024	11,250
4/28/2024	10,850	8/25/2024	11,475	12/22/2024	11,425
5/5/2024	10,775	9/1/2024	11,450	12/29/2024	11,375
				1/5/2025	11,075
				1/12/2025	10,825

1/19/2025	11,425
1/26/2025	11,500

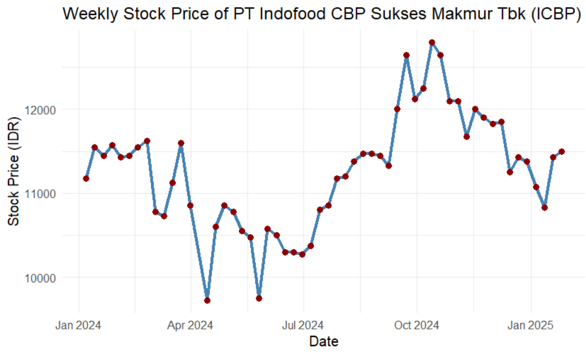

Figure. 2 Graph of PT Indofood CBP Sukses Makmur Tbk Stock Price

B. *Stationary Check*

Before processing the data, it is necessary to confirm whether the data is stationary using the Augmented Dickey-Fuller (ADF) test method in R Studio. If the p-value obtained is below 0.05, then the data can be considered stationary. In Figure 2, the plot of PT Indofood CBP Tbk weekly stock price is displayed before performing differencing. Based on the result of the Augmented Dickey-Fuller Test, **the p-value is 0.7289**. Since this value exceeds the significance level of 0.05, it indicates that **the data is not stationary**.

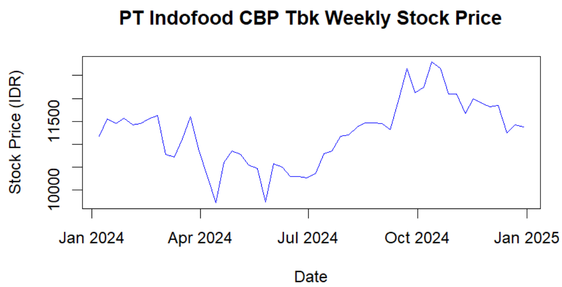

Figure. 3 Plot of PT Indofood CBP Sukses Makmur Tbk Stock Price

To make the data stationary, differencing is required using the diff(data) function in R Studio. In Figure 3, the plot of the first difference of PT Indofood CBP Tbk stock price is shown after performing the first differencing. From the Augmented Dickey-Fuller Test, the p-value obtained after first differencing is **0.02139**. As this p-value is less than 0.05, it indicates that the data has become **stationary** and the order **d = 1** will be used in the ARIMA model.

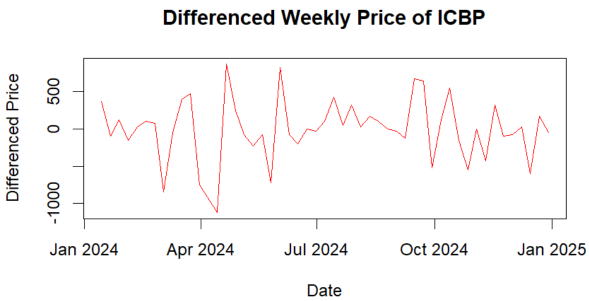

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Figure. 4 Plot of First Difference PT Indofood CBP Sukses Makmur Tbk Stock Price

C. Model Specification

The ARIMA model can be specified by examining the Auto-Correlation Function (ACF) and Partial Auto-Correlation Function (PACF) plots of the data after differencing. In Figure 4, the ACF and PACF plots of the first difference of PT Indofood CBP Tbk stock price are displayed.

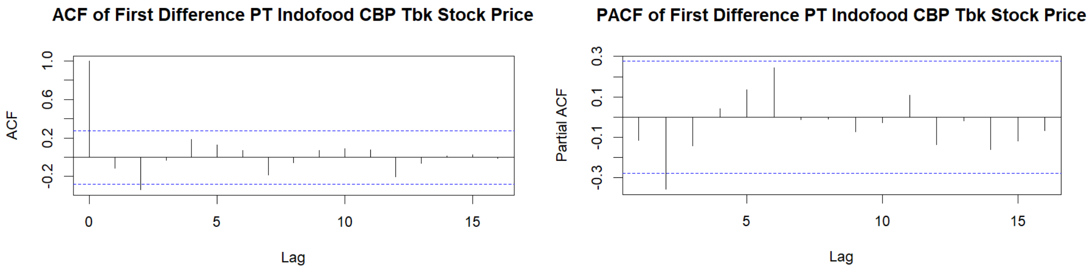

Figure. 5 Plot of ACF and PACF First Difference of PT Indofood CBP Sukses Makmur Tbk Stock Price

Based on the ACF and PACF plots of the first differenced data, the ACF cuts off at lag 2 and the PACF also cuts off at lag 2. This indicates that the appropriate maximum values for the ARIMA model parameters are **p = 2**, **d = 1**, and **q = 2**. Therefore, several combinations of ARIMA(p,d,q) models are considered within this range, as shown in the following table.

TABEL 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

D. Parameter Estimation

The coefficients of the Autoregressive (AR) and Moving Average (MA) components are estimated using the ARIMA model. AR terms are represented by φ with order *p*, and MA terms by θ with order *q*. The parameter estimates, along with the Log Likelihood and Akaike Information Criterion (AIC), are presented in the table below. These values were obtained using RStudio through the model summary output.

TABEL 3
PARAMETER ESTIMATION FOR ARIMA MODEL

ARIMA Model	AR1	AR2	MA1	MA2	Log Likehood	AIC
ARIMA (0,1,0)					-370.94	743.88
ARIMA (0,1,1)			-0.3233		-368.88	743.76
ARIMA (0,1,2)			-0.1555	-0.2418	-367.99	741.98
ARIMA (1,1,0)	-0.1146				-370.61	745.21

ARIMA (1,1,1)	0.3196		-0.5826		-369.09	744.18
ARIMA (1,1,2)	-0.1317		-0.0432	-0.2690	-367.92	743.84
ARIMA (2,1,0)	-0.1543	-0.3499			-367.27	740.54
ARIMA (2,1,1)	0.0395	-0.3332	-0.2277		-366.96	741.92
ARIMA (2,1,2)	0.6141	-0.7391	-0.8905	0.6703	-365.37	740.75

E. *Residual Analysis*

To identify the most appropriate ARIMA model, both the Shapiro-Wilk Test and the Ljung-Box Test were used as diagnostic tools for residual analysis. An ARIMA model is considered acceptable if the p-values from both tests are greater than 0.05, indicating that the residuals are normally distributed and exhibit no significant autocorrelation. Table 4 summarizes the results for nine ARIMA models.

TABEL 4
RESULT OF RESIDUAL ANALYSIS

No.	ARIMA Model	Shapiro Test	Ljung-Box Test	AIC	Result
1	ARIMA (0,1,0)	0.05370	0.20055	743.88	Passed
2	ARIMA (0,1,1)	0.03108	0.12624	743.76	Not Passed
3	ARIMA (0,1,2)	0.04054	0.75740	741.98	Not Passed
4	ARIMA (1,1,0)	0.01987	0.12311	745.21	Not Passed
5	ARIMA (1,1,1)	0.03110	0.36308	744.18	Not Passed
6	ARIMA (1,1,2)	0.03908	0.72534	743.84	Not Passed
7	ARIMA (2,1,0)	0.05489	0.78766	740.54	Passed
8	ARIMA (2,1,1)	0.04477	0.88957	741.92	Not Passed
9	ARIMA (2,1,2)	0.03554	0.99852	740.75	Not Passed

Among them, only ARIMA(0,1,0) and ARIMA(2,1,0) satisfy the required conditions, with both tests showing p-values above the threshold. These models passed the residual diagnostics and will be further evaluated using forecasting accuracy measures.

F. *Forecast*

TABEL 4
FORECASTING VALUE OF ARIMA (0,1,0)

Date	Actual Data	Predicted Data	Lower Bound	Upper Bound
1/5/2025	11075	11500	10759.48	12240.52
1/12/2025	10825	11500	10452.75	12547.25
1/19/2025	11425	11500	10217.39	12782.61
1/26/2025	11500	11500	10018.97	12981.03

TABEL 5

FORECASTING VALUE OF ARIMA (2,1,0)

Date	Actual Data	Predicted Data	Lower Bound	Upper Bound
1/5/2025	11075	10878.	10855.30	10900.95
1/12/2025	10825	10985.	10956.54	11012.47
1/19/2025	11425	11575.	11546.99	11603.71
1/26/2025	11500	11297.	11267.16	11326.12

Based on the forecasting values presented in TABLE 4 and TABLE 5, the most appropriate ARIMA model for forecasting can be identified by comparing the error values (MSE, RMSE, MAE, and MAPE) between the models.

TABEL 6

ERROR MEASURED FROM ARIMA MODELS

ARIMA Model	MSE	RMSE	MAE	MAPE
ARIMA (0,1,0)	160468.8	400.5855	293.75	2.68%
ARIMA (2,1,0)	32029.5	178.9679	177.50	1.58%

Based on Table 6, the ARIMA(2,1,0) model achieves the lowest error values compared to the other models (MSE = 32,029.5; RMSE = 178.9679; MAE = 177.50; MAPE = 1.58%). This indicates that **ARIMA(2,1,0)** is the most accurate model for forecasting the stock prices in the given analysis.

From the parameter estimates provided in Table 3, the model has:

- AR1 = -0.1543
- AR2 = -0.3499

The ARIMA(2,1,0) model can be expressed in the following form:

$$W_t = -0.1543W_{t-1} - 0.3499W_{t-2} + e_t$$

Let

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

Then, the equation becomes:

$$Y_t - Y_{t-1} = -0.1543(Y_{t-1} - Y_{t-2}) - 0.3499(Y_{t-2} - Y_{t-3}) + e_t$$

Expanding and simplifying the terms :

$$Y_t = Y_{t-1} - 0.1543Y_{t-1} + 0.1543Y_{t-2} - 0.3499Y_{t-2} + 0.3499Y_{t-3} + e_t$$

$$Y_t = 0.8457Y_{t-1} - 0.1956Y_{t-2} + 0.3499Y_{t-3} + e_t$$

Final Model Equation:

$$\boxed{Y_t = 0.8457Y_{t-1} - 0.1956Y_{t-2} + 0.3499Y_{t-3} + e_t}$$

This final model combines the previous two lagged values of the stock price to generate forecasts, with high accuracy reflected by a low MAPE of 1.58%. Such precision makes it a valuable tool for investors aiming to make informed decisions regarding stock transactions. Accurate forecasts enable better timing of buying or selling actions, aiding in portfolio optimization and improved risk mitigation. Moreover, the model's output can support corporate financial planning by aligning internal strategies with expected market behaviors. Reliable predictions also help businesses stay agile in the face of economic shifts and maintain competitive advantage [1].

Figure 5 illustrates the ARIMA (2,1,0) forecast of PT Indofood Cbp Sukses Makmur Tbk (ICBP) stock prices for the period from January 1, 2024, to January 26, 2025.

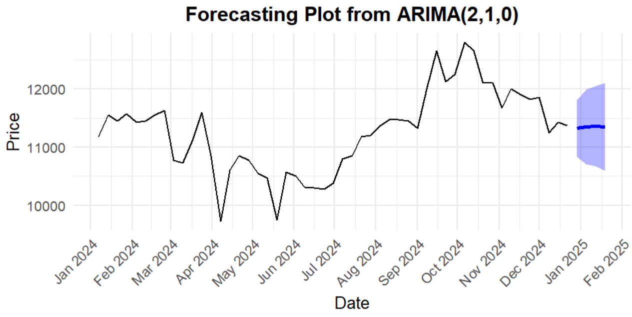

Figure. 6 Forecasting Plot from ARIMA (2,1,0)

IV. Conclusion

Stock price forecasting has been done for PT Indofood Cbp Sukses Makmur Tbk (ICBP) for the next 4 weeks from January 5, 2025 to January 26, 2025 with original stock price data from January 01, 2024 to December 31, 2024 with total 51 data obtained from Investing.com website. Using Box-Jenkins Method and processed using R Studio, it was found that the ARIMA (2,1,0) 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:

$$\boxed{Y_t = 0.8457Y_{t-1} - 0.1956Y_{t-2} + 0.3499Y_{t-3} + e_t}$$

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, if there are significant external variables that could impact stock prices, in order to improve the accuracy of the forecast.

References

[1] G. E. P. Box, G. M. Jenkins, G. C. Reinsel, and G. M. Ljung, *Time Series Analysis: Forecasting and Control*, 5th ed. Hoboken, NJ: Wiley, 2015.

[2] S. D. Laskarjati and I. S. Ahmad, “Perbandingan Peramalan Harga Saham menggunakan Autoregressive Integrated Moving Average (ARIMA) dan Fuzzy Time Series Markov Chain (Studi Kasus: Saham PT Indofood CBP Sukses Makmur Tbk),” *J. Sains dan Seni ITS*, vol. 11, no. 6, pp. 397–404, 2022.

[3] R. T. Dewanti, E. Zukhronah, and W. Sulandari, “Peramalan Harga Saham PT Indofood Sukses Makmur Tbk Menggunakan Model Hibrida Singular Spectrum Analysis (SSA) – Autoregressive Integrated Moving Average (ARIMA),” *J. Gaussian*, vol. 13, no. 2, pp. 270–279, 2024.

[4] Investing.com, “PT Indofood CBP Sukses Makmur Tbk [ICBP] Historical Data,” 2024.

[5] A. I. S. Wardhani and M. R. Yudhanegara, "Forecasting Weekly Stock Price of PT. Aneka Tambang Tbk (ANTM) Using ARIMA Box-Jenkins Method," *Journal of Actuarial, Finance and Risk Management (JAFRM)*, vol. 3, no. 2, pp. –, Dec. 2024

[6] R. J. Hyndman and G. Athanasopoulos, Forecasting: Principles and Practice, 3rd ed. Melbourne, Australia: OTexts, 2021.

[7] C. D. Lewis, Industrial and business forecasting methods: A Radical guide to exponential smoothing and curve fitting. London: Butterworth Scientific, 1982.

[8] H. Wickham and G. Grolemund, *R for Data Science: Import, Tidy, Transform, Visualize, and Model Data*. Sebastopol, CA, USA: O'Reilly Media, 2017.

[9] H. Akaike, “A new look at the statistical model identification,” IEEE Trans. Automat. Control, vol. 19, no. 6, pp. 716–723, Dec. 1974

[10] S. S. Shapiro and M. B. Wilk, “An analysis of variance test for normality (complete samples),” Biometrika, vol. 52, no. 3–4, pp. 591–611, Dec. 1965.