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MODELING THE IDX30 STOCK INDEX USING STEP FUNCTION INTERVENTION ANALYSIS

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ABSTRACT

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The significant decline in the IDX30 stock index occurred due to an intervention, namely the COVID-19 pandemic, which affected market stability and investment decisions. This study aims to model and forecast the IDX30 stock index using intervention analysis with a step function, which is very suitable for capturing long-term external shocks. The methodology used includes the ARIMA (AutoRegressive Integrated Moving Average) model combined with step function intervention analysis to account for structural changes due to external disturbances. The data used is sourced from investing.com, consisting of weekly IDX30 stock index prices from January 2019 to December 2023. The results show that the COVID-19 pandemic significantly impacted the IDX30 index, causing a drastic decline. The best model identified is ARIMA (1,2,1) with intervention parameters b = 0, s = 0, and r = 1. The forecasting results range from Rp. 488 to Rp. 505, with a Mean Absolute Percentage Error (MAPE) of 1.9404%, which shows the forecasting results are very good, indicating high forecasting accuracy. These findings highlight the effectiveness of intervention analysis in modeling financial time series data affected by external disturbances.

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1. INTRODUCTION

In the era of globalization, most countries, especially Indonesia, pay considerable attention to the capital market. Given the dual role of the capital market as a means of investment and as a source of business funding for companies that want to obtain funds from the public, the capital market plays an important role in a country's economy. In carrying out investment activities in the capital market, there are many financial tools that can be used, one of which is stocks [1].

Shares are securities that prove shareholders' capital participation in a company. These letters give shareholders the right to receive a portion of the company's profits. The indicator used to show how much the price changes in the stock market over a certain period of time is called a stock index, one of which is IDX30. IDX30 is an index that evaluates the price performance of 30 stocks with high liquidity, high capitalization, and strong company fundamentals [2].

Stocks listed on the Indonesia Stock Exchange experienced significant increases and decreases. However, in early March 2020, various stock indices, including the IDX30, experienced a decline and reached a low of Rp. 311.88 at the end of March due to the COVID-19 pandemic [3]. The Severe Acute Respiratory Syndrome Coronavirus-2 virus has a faster rate of development that can lead to more serious illness and organ failure.

The Indonesian government has implemented the Large-Scale Social Restrictions (PSBB) program in an effort to contain the spread of the coronavirus in Indonesia. This has led to the cessation of community social activities and has an impact on the capital market and economy, as well as other aspects of people's social life [4]. The fear of the virus spreading triggered panic among foreign investors who offloaded their shares, resulting in a sharp decline in global exchanges. Although not a direct economic event, the impact of COVID-19 on the financial sector has been profound. The effects caused by the coronavirus destabilized the macroeconomy and caused losses in several investment products or instruments [5].

COVID-19 is an out-of-control event or so-called intervention that affects the IDX30 stock index, causing fluctuations. In addition to potential profits, buying and selling in the capital market also has considerable risk, especially if there is intervention. An effort that can be made to minimize the possibility of loss is by forecasting the stock index. Forecasting is a key tool in financial risk management, allowing investors to anticipate market trends. Forecasting is a technique for estimating conditions that will occur in the future [6]. Traditional time series models, such as ARIMA, provide a structured approach to predicting stock price movements. However, when external shocks such as COVID-19 occur, traditional models alone may not be sufficient. Intervention analysis, specifically the step function intervention method, improves the ARIMA model by incorporating structural shifts caused by external events so that it can better explain the impact of the intervention.

Some previous research has been made, such as research on the analysis of the intervention model of the number of airplane passengers at Sultan Hasanuddin Airport, which found that the analysis of the response pattern of the number of airplane passengers produced an intervention effect when the intervention impact occurred [7]. There is also research on forecasting tourism demand during the COVID-19 pandemic with the ARIMAX approach and intervention modeling. It was found that the intervention model provides the most accurate forecasting when compared to ARIMAX [8]. Another study comparing the goodness of the step function intervention model with ARIMA Box-Jenkins found that the intervention model with a step function is a better model [9]. In addition, previous research also produced predictions of IDX30 stock index prices in Indonesia during the COVID-19 pandemic with ARIMA. The test results using IDX30 stock closing price data obtained a MAPE of 7.96% [10]. There is also research on “Intervention analysis of COVID-19 pandemic impact on timber price in selected markets”. The results show that intervention analysis and structural break analysis have proven to be good tools for studying the impact of external shocks, such as the COVID-19 pandemic, on timber price movements [11]. Based on the previous description, this study models the IDX30 stock index using ARIMA with step function intervention analysis to assess the impact of COVID-19 and improve forecasting accuracy.

2. RESEARCH METHODS

2.1 Stationary

Time series analysis has the assumption of stationarity. A stationary model is considered a condition that has probabilistic and remains in equilibrium or statistical stability that does not change over time. In time series data, stationarity is indicated by constant variance and mean values [12]. When time series data periodically fluctuates with a fixed variance, the data is said to be stationary in variance. In other words, the value of the variance is fixed for each t. The test for data stationarity in variance can also use the Levene test [13]. If there is data non-stationarity in variance, a Box-Cox transformation process can be performed. The Box-Cox transformation is a method of transformation of the response, namely by lifting $\mathrm{Z_t}$ with λ, so that it can be written as Z_t^{λ} with lambda (λ) is the value of the transformation parameter. If $\lambda = 1$ means that no transformation is required; in other words, the time series data is stationary in variance. Stationarity in the mean can be determined using the unit root test, namely the Augmented Dickey-Fuller (ADF) test. Data that is not stationary in the mean can be overcome by differencing. This aims to make the data stationary, both at the first and second differencing stages [14].

2.2 Intervention Analysis

An external event, such as a vacation, religious holiday, sales promotion, or policy change, can often affect the pattern of time series data. In such time series data, there is usually a sharp increase or decrease. These events are called interventions. A method that can be used to address the impact of interventions on time series is intervention analysis [15]. Measuring the magnitude and duration of the effect that occurs due to an intervention in time series data is the goal of intervention analysis. Intervention analysis is divided into two types of variables, namely pulse function and step function. A step function is an intervention variable where the intervention occurs at time t and so on over a long period of time. The intervention occurrence time in the pulse function only takes place at time t. The model for intervention analysis is generally formulated as follows [16].

$$Z_t = f(I_t) + Y_t \tag{1}$$

Y_t is an ARIMA model without the influence of intervention, and $f(I_t)$ is a function of the t time intervention variable. The function of the intervention variable is represented by $\frac{\omega_s(B)}{\delta_r(B)}$ and B is a backshift operator that causes the data to go back one period.

The ARIMA model on the data before the intervention will be used as a reference to identify the intervention order. In the process of identifying the order of intervention, the leftover response graph is used. The conditions are as follows [17]:

1. Order b is calculated based on the start time of the intervention effect, characterized by a lag that is outside the significance limit. If the intervention effect is felt immediately at the time of the intervention, then order b is zero. If the effect is felt after one period of the intervention, then order b is one. Order b is two, if the effect is felt after two periods of intervention, and so on.
2. Order s is the length of time delay until the data stabilizes again, characterized by the start of a decline from the previous lag. For example, if the intervention occurs at time T and at time $T + 1$ the side response is not as small as at time T, then at time $T + 2$ the response is smaller than the previous time, namely, time $T + 1$, then order s is worth one.
3. Order r can be known through the pattern of the leftover response graph. If the graph does not show any pattern, it is said that order r is zero. If the leftover response graph has an exponential pattern, then order r is one. Meanwhile, if the leftover response graph shows a sine or cosine pattern, then order r is worth two.

2.3 Mean Absolute Percentage Error (MAPE)

The results of a forecast often show different results from the actual conditions, which is due to the presence of forecasting errors. There are several methods for calculating forecasting accuracy, one of which is Mean Absolute Percentage Error. MAPE is a method of calculating the percentage of forecasting error compared to the actual value. MAPE produces a value in the form of a percentage, making it easier to interpret. MAPE is formulated as follows [18]:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Z_t - \hat{Z}_t}{Z_t}\right| \times 100\% \tag{2}$$

The model that has the smallest MAPE value is a very good forecasting model. In forecasting, there is a measure of the model's ability that can be seen in the following MAPE value interval [19]:

Table 1. MAPE Value

MAPE	Decision
<10%	Excellent forecasting ability
10% - 20%	Good forecasting ability
20% - 50%	Fair forecasting ability
>50%	Poor forecasting ability

Source*: Pradani dkk (2021)*

2.4 Data Sources and Research Variables

The data used in the study is secondary data taken from the website https://www.investing.com. The variables used are weekly historical price data for the IDX30 stock index (Z_t) from January 2019 to December 2023, with the COVID-19 pandemic (I_t) as an intervention variable that occurred on March 9, 2020.

2.5 Analysis Method

Data analysis in this study uses R software, with the following steps**:**

1. Collecting data.
2. Input data.
3. Data exploration using IDX30 stock index time series data plots.
4. Determined the intervention point and grouped the 2019 to 2022 data into two groups based on the intervention time.
   a. Data before intervention, namely January 6, 2019, to March 8, 2020.
   b. Data from when the intervention occurred until the last data, namely March 15, 2020, to December 25, 2022.
5. Perform ARIMA modeling on the data before intervention.
   a. Checking data stationarity in variance using Levene's test and data stationarity in average using the Augmented Dickey Fuller Test or ADF Test.
   b. Model identification before intervention using ACF and PACF plots.
   c. Model identification by estimating model parameters and selecting the best model based on the smallest AIC value.
   d. Perform white noise residual assumption test using Ljung-Box Test and normal distribution residual assumption test using Kolmogorov-Smirnov test.
   e. Perform prediction using the selected ARIMA model.

6. Building an intervention model
   a. Identify the value of the order (b, r, s) using the leftover response graph obtained from the difference between the actual data subtracted from the predicted data using the ARIMA model before the intervention.
   b. Perform parameter estimation of the intervention model
   c. Test the assumptions of white noise and normally distributed residuals on the intervention model.
7. Forecast the IDX30 stock index using the intervention model and calculate the level of forecasting accuracy using Mean Absolute Percentage Error (MAPE). Forecasting is carried out from January 1 to December 31, 2023.
8. Interpretation of results

3. RESULTS AND DISCUSSION

3.1 Data Exploration

Data exploration is the process of recognizing data before it is processed with the aim of understanding the pattern of data. Data exploration in this study was carried out through plots. The data used is the weekly historical price of the IDX30 stock index for the period January 2019 to December 2023. The data exploration is described in **Figure 1** below:

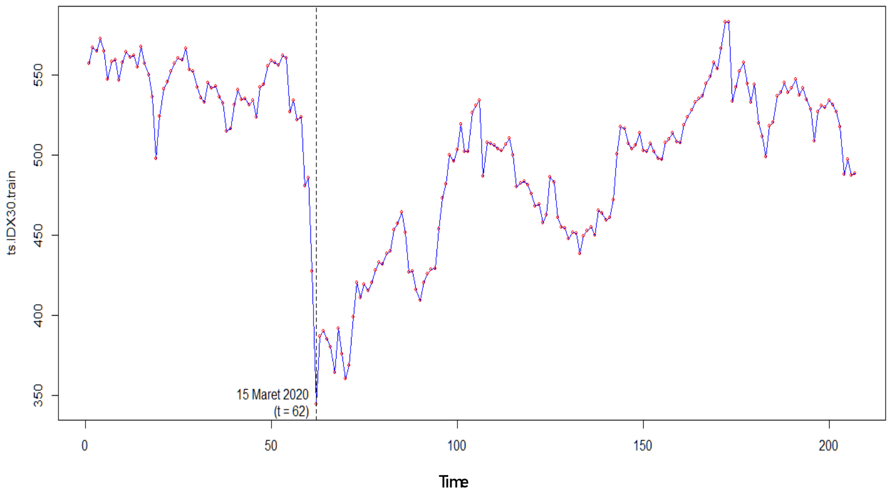
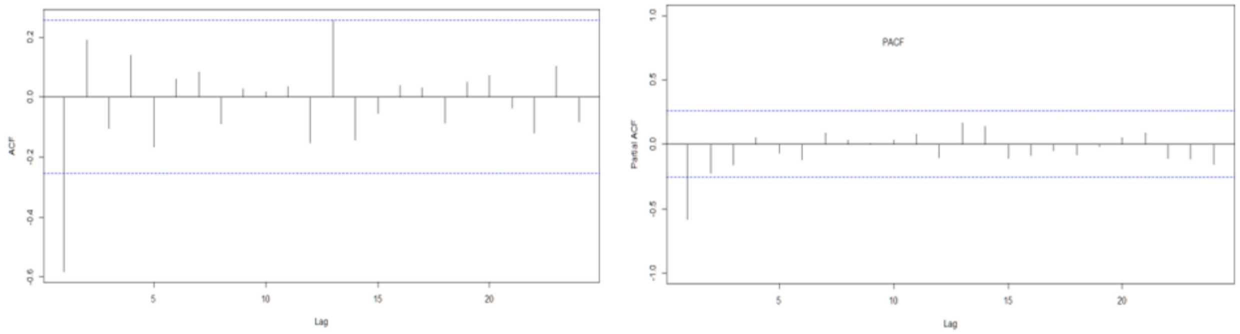


Figure 1. Plot of IDX30 Before 2nd Differencing Intervention
***Source:* RStudio**

Based on **Figure 1**, it can be seen visually that the data has been stationary, characterized by data patterns that tend to move towards the average or pass through the horizontal axis. This has also been proven previously using the Augmented Dickey-Fuller test.

3.2 ARIMA Model Identification

After checking the data stationarity in variance and mean, the next step is to determine the ARIMA model on the IDX30 stock index data before the intervention, namely the period January 6, 2019, to March 8, 2020 ($t < 62$) with $n = 61$. The results obtained can be seen through the ACF and PACF plots in **Figure 2** below:



(a) (b)

Figure 2. (a) Differencing ACF Plot, (b) Differencing PACF Plot
***Source:* RStudio**

The ACF plot and the PACF plot in Figure 2 are used in determining the tentative ARIMA model, known from the lags that have been significant in this case, obtained after differencing twice. From the ACF and PACF plots above, it is known that both cut off at the first lag. So that 3 temporary models are obtained, namely IMA (2,1), ARI (1,2), and ARIMA (1,2,1).

3.3 Model Parameter Estimation Before Intervention

The next step is to estimate the parameters of the temporary ARIMA model. The estimated value generated from each temporary model can be seen in Table 2 below:

Table 2. Model Parameter Estimation Before Intervention

Model	Parameter	Estimate	AIC
ARI (1,2)	$\boldsymbol{\phi_1}$	-0.6879	496.68
IMA (2,1)	$\boldsymbol{\theta_1}$	-0.8916	490.51
ARIMA (1,2,1)	$\boldsymbol{\phi_1}$	-0.3061	489.55
	$\boldsymbol{\theta_1}$	-0.7399	

Based on Table 2, the estimated parameters and AIC value of each temporary model can be seen. Of the three models, the best model is the ARIMA (1,2,1) model. This model is said to be the best because it has the smallest AIC value compared to the other two models, which is 489.55. The ARIMA (1,2,1) model equation can be written as follows.

$$Y_t = \frac{\theta_q(B)}{\phi_p(B)(1-B)^d} e_t$$

$$Y_t = \frac{(1-\theta_1 B - \ldots - \theta_q B^q)}{(1-\phi_1 B - \ldots - \phi_p B^p)(1-B)^d} e_t$$

$$Y_t = \frac{(1-\theta_1 B)}{(1-\phi_1 B)(1-B)^2} e_t \tag{3}$$

3.4 Residual Assumption Test Before Intervention

A model can be said to be a feasible model if the residual white noise and normality assumptions have been met. To find out whether the model meets the white noise assumption, it can be done using the Ljung-Box test. As for testing the normality of a model, it can be done with the Kolmogorov-Smirnov test. The results of the two tests are presented in Table 3 below:

Table 3. Ljung-Box Test and Kolmogorov-Smirnov Test on Model Before Intervention

Residual Assumption Test	*p*-value
Ljung-Box Test	0.9539
Kolmogorov-Smirnov Test	0.2805

Based on **Table 3**, the p-value of the two residual assumption tests can be seen. With a significance level of alpha = 5%, the Ljung-Box test results are obtained with a p-value of 0.9539 > 0.05 and the Kolmogorov-Smirnov test result with a p-value of 0.2805 > 0.05. So that the ARIMA (1,2,1) model has met the assumptions of white noise and normal distribution. Thus, it is concluded that the model is suitable for use.

3.5 Model Prediction Results Before Intervention

After obtaining a model that meets both assumptions, namely the white noise assumption and the normality assumption, the next step is to predict the selected model, namely ARIMA (1,2,1). The model prediction results before intervention are presented in **Table 4** below:

Table 4. Model Prediction Results Before Intervention

Date	T	Prediction
January 06, 2019	1	556.87
January 13, 2019	2	567.86
January 20, 2019	3	573.03
January 27, 2019	4	570.38
February 03, 2019	5	575.26
⋮	⋮	⋮
February 09, 2020	57	525.75
February 16, 2020	58	518.33
February 23, 2020	59	517.38
March 01, 2020	60	478.36
March 08, 2020	61	470.75

From the prediction results above, the prediction accuracy value of the model before intervention, using the Mean Absolute Percentage Error (MAPE) value, is presented in **Table 5** below:

Table 5. Model Prediction Accuracy Before Intervention

Model	MAPE (%)
Arima(1,2,1)	1.8893

Based on **Table 5**, the prediction MAPE value of the ARIMA (1,2,1) model is 1.8893%. This indicates that the prediction results of the model are very good because they produce a MAPE < 20.

3.6 Identification of Intervention Order

After getting the best model on the data before the intervention, the next step is to analyze the IDX30 stock index data by adding the intervention that occurred at $T = 62$. This intervention analysis uses a step function because the COVID-19 pandemic event has an influence on a long enough period. The analysis is carried out by identifying the intervention order value obtained by looking at the residual response graph. The residual response graph can be seen in **Figure 3** below:

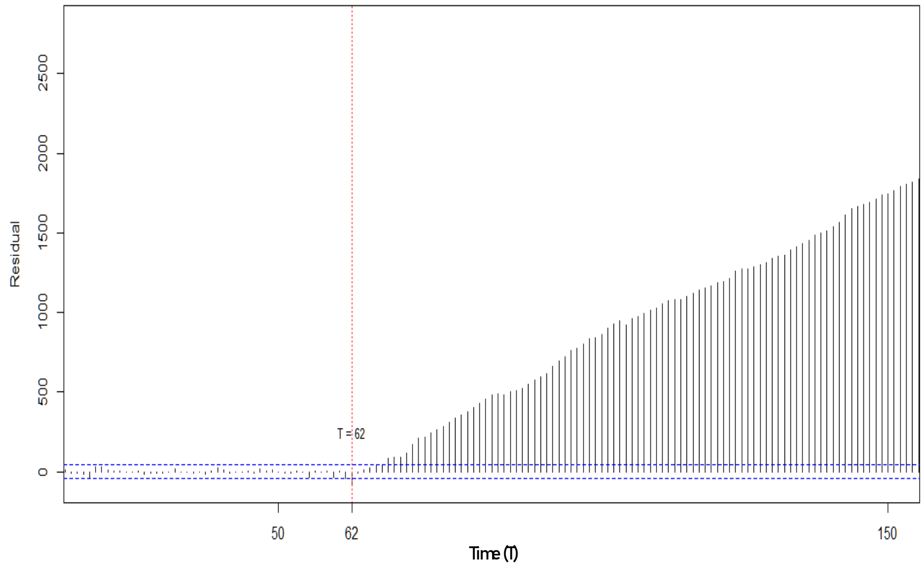


Figure 3. Intervention Residual Response Graph
***Source:* RStudio**

Based on **Figure 3**, it is observed that the first lag of the residual response exceeds the significance limit at $T = 62$. Therefore, it can be concluded that the order $b = 0$. Meanwhile, for the length of the intervention effect, until the next lag response decreases or is smaller than the previous lag, occurs at $T + 1$ in this graph, so $s = 0$. It is also known that the pattern formed from the response graph is an exponential pattern, so it can be said that the order $r = 1$. Furthermore, the intervention order value obtained can be written as follows:

$$f(I_t) = \frac{\omega_s(B)}{\delta_r(B)} B^b, \qquad I_t = \frac{\omega_0(B)}{\delta_1(B)} B^0 S_t{}^{(62)} \tag{4}$$

3.7 Parameter Estimation of Intervention Model

After identifying the intervention order, the next step is to estimate the parameters of the intervention model. The estimated parameters consist of δ_1, ω_0, ϕ_1, and θ_1. The results of the parameter estimation test are presented in **Table 6** and **Table 7** below:

Table 6. Intervention Model Parameter Estimation

Parameter	Estimate
$\boldsymbol{\delta_1}$	3.0585×10^{-13}
$\boldsymbol{\omega_0}$	-37.484

Based on **Table 6**, it is known that the estimated value of each parameter is $\delta_1 = 3.0585\ x\ 10^{-13}$ and $\omega_0 = -37.484$. Furthermore, these values will be used in the estimation of the final intervention model parameters. This aims to obtain the parameter estimation values of ϕ_1 and θ_1 as in the following table:

Table 7. Parameter Estimation of the Final Intervention Model

Parameter	Estimate
$\boldsymbol{\phi_1}$	-0.0185
$\boldsymbol{\theta_1}$	-1.0000

Based on **Table 7**, the estimated values of each parameter are $\phi_1 = -0.0185$ and $\theta_1 = -1.0000$. The estimated values of these parameters are then combined with the previous parameter coefficients in creating an intervention model. The intervention model can be written as follows, as in **Equation (1)**:

$$Z_t = f(I_t) + Y_t$$

With the ARIMA (1,2,1) model equation obtained previously, **Equation (3)**:

$$Y_t = \frac{(1-\theta_1 B)}{(1-\phi_1 B)(1-B)^2} e_t$$

Where, for the intervention model, the step function $f(I_t) = \frac{\omega_s(B)}{\delta_r(B)} B^b S_t^{(T)}$ with $b = 0$, $s = 0$ and $r = 1$, $\omega_s(B) = (\omega_0 - \omega_1 B - \omega_2 B^2 - \cdots - \omega_s B^s)$, and $\delta_r(B) = (1 - \delta_1 B - \delta_2 B^2 - \cdots - \delta_r B^r)$ then it can be written as follows:

$$Z_t = \frac{\omega_0(B)}{\delta_1(B)} B^0 S_t^{(62)} + \frac{(1-\theta_1 B)}{(1-\phi_1 B)(1-B)^2} e_t$$

$$Z_t = \frac{\omega_0}{(1-\delta_1 B)} S_t^{(62)} + \frac{(1-\theta_1 B)}{(1-\phi_1 B)(1-B)^2} e_t$$

$$\vdots$$

$$\begin{aligned} Z_t &= 2Z_{t-1} - Z_{t-2} + \phi_1 Z_{t-1} - 2\phi_1 Z_{t-2} + \phi_1 Z_{t-3} + \delta_1 Z_{t-1} - 2\delta_1 Z_{t-2} + \delta_1 Z_{t-3} - \delta_1\phi_1 Z_{t-2} \\ &\quad + 2\delta_1\phi_1 Z_{t-3} - \delta_1\phi_1 Z_{t-4} + \omega_0 S_t^{(62)} - 2\omega_0 S_{t-1}^{(62)} + \omega_0 S_{t-2}^{(62)} - \omega_0\phi_1 S_{t-1}^{(62)} \\ &\quad + 2\omega_0\phi_1 S_{t-2}^{(62)} - \omega_0\phi_1 S_{t-3}^{(62)} + e_t - \delta_1 e_{t-1} - \theta_1 e_{t-1} + \delta_1\theta_1 e_{t-2} \\ Z_t &= (2 + \phi_1 + \delta_1) Z_{t-1} - (1 + 2\phi_1 + 2\delta_1 + \delta_1\phi_1) Z_{t-2} + (\phi_1 + \delta_1 + 2\delta_1\phi_1) Z_{t-3} \\ &\quad - \delta_1\phi_1 Z_{t-4} + \omega_0 S_t^{(62)} - (2 + \phi_1)\omega_0 S_{t-1}^{(62)} + (1 + 2\phi_1)\omega_0 S_{t-2}^{(62)} \\ &\quad - \omega_0\phi_1 S_{t-3}^{(62)} + e_t - (\delta + \theta_1) e_{t-1} + \delta_1\theta_1 e_{t-2} \end{aligned} \quad (5)$$

With the help of Excel software, the final intervention model of the step function is obtained as follows.

$$\begin{aligned} Z_t = {} & 1.9815 Z_{t-1} - 0.963 Z_{t-2} - 0.0185 Z_{t-3} + 5.6582 \times 10^{-15} Z_{t-4} - 37.484 S_t^{(62)} + 74.275 S_{t-1}^{(62)} \\ & - 36.097 S_{t-2}^{(62)} - 0.6935 S_{t-3}^{(62)} + e_t + 1.0000 e_{t-1} - 3.0585 \times 10^{-13} e_{t-2} \end{aligned}$$

with, $I_t = S_t^{(62)} = \begin{cases} 0, t < 62 \\ 1, t \geq 62 \end{cases}$.

3.8 Residual Assumption Test of Intervention Model

If the white noise and normally distributed residual assumptions have been met, then a model can be said to be a good model. Just like testing the residual assumptions of the model before the intervention, the Ljung-Box test is used to determine whether the model meets the white noise assumption, and also the Kolmogorov-Smirnov test to test the normality of an intervention model. The results of both tests are presented in **Table 8** below:

Table 8. Ljung-Box Test and Kolmogorov-Smirnov Test on The Intervention Model

Residual Assumption Test	p-value
Ljung-Box Test	0.9636
Kolmogorov-Smirnov Test	0.1044

Based on **Table 8**, the p-value of the two residual assumption tests is known. With a significance level of alpha = 5%, the Ljung-Box test results are obtained with a p-value of 0.9636 > 0.05 and the Kolmogorov-Smirnov test results with a p-value of 0.1044 > 0.05. This shows that the step function intervention model has fulfilled the two required assumptions. So, with this, it can be concluded that the model is suitable for use in forecasting.

3.9 Intervention Model Prediction Results

The next step is to predict the model after the intervention. The prediction results of the intervention model are presented in **Table 9** below:

Table 9. Intervention Model Prediction Results

Date	T	Prediction
January 06, 2019	1	556.87
January 13, 2019	2	567.86
⋮	⋮	⋮
March 01, 2020	60	479.90
March 08, 2020	61	483.91
March 15, 2020	62	342.70
⋮	⋮	⋮
December 18, 2022	206	497.05
December 25, 2022	207	487.32

From the prediction results above, the accuracy value of the intervention model prediction using the Mean Absolute Percentage Error (MAPE) value is presented in Table 10 below:

Table 10. Intervention Model Prediction Accuracy

	MAPE (%)
Intervention Model	1.8977

Based on Table 10, the prediction MAPE value of the intervention model is 1.8977%. This indicates that the model prediction results are very good because they produce a MAPE < 20%. When compared to the prediction MAPE value of the ARIMA (1,2,1) model, which is 1.8977%, it can be concluded that the prediction MAPE value in the intervention model is greater than the prediction MAPE value in the model before the intervention, 1.8893%. This can be assumed as the cause of the intervention effect, namely the COVID-19 pandemic.

3.10 Intervention Model Forecasting Results

After obtaining the best intervention model that has met the residual assumption test, the model is suitable for forecasting. Forecasting is carried out using data from January 1 to December 31, 2023. The results of the intervention model forecasting are presented in Table 11 below:

Table 11. Intervention Model Forecasting Results

Date	T	Actual Data	Forecasting
January 01, 2023	208	474.97	488.53
January 08, 2023	209	471.05	488.94
January 15, 2023	210	491.05	489.35
⋮	⋮	⋮	⋮
December 17, 2023	258	491.41	505.28
December 24, 2023	259	495.21	505.55
December 31, 2023	260	501.72	505.82

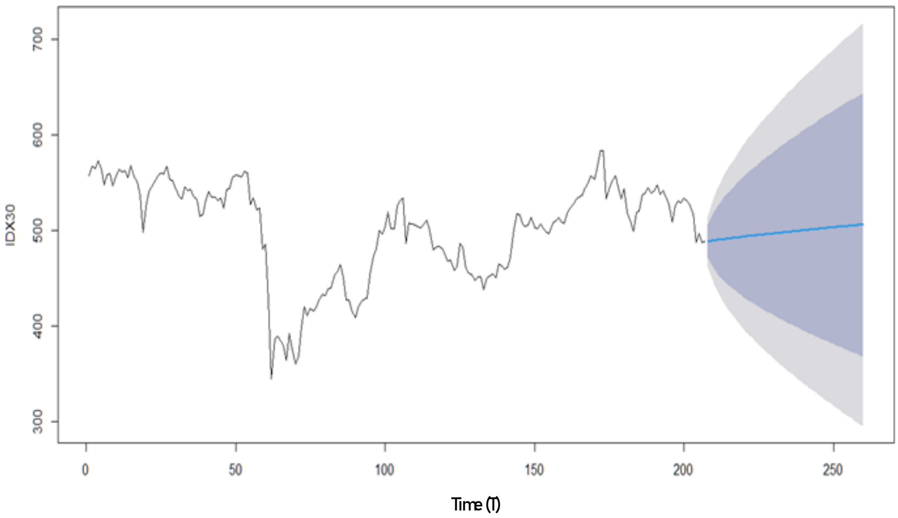


Figure 4. Plot of Intervention Model Forecasting Results
***Source:* RStudio**

Based on **Figure 4**, it is known that the forecasting results of the intervention model tend to be constant. The value of the IDX30 stock index in 2023 rises slowly every week in the range of Rp. 488 to Rp. 505. From the forecasting results, it can also be seen that the forecasting accuracy value using the MAPE value is as in **Table 12** below:

Table 12. Intervention Model Forecasting Accuracy

	MAPE (%)
Validation	1.9404

Based on **Table 12**, the MAPE value of the intervention model is 1.9404%. Because MAPE < 20%, it can be concluded that the model forecasting results are very good.

4. CONCLUSIONS

Based on the discussion presented earlier, it can be concluded that the best model obtained from the IDX30 stock index data is ARIMA (1,2,1) with the intervention order obtained, namely $b = 0$, $s = 0$ and $r = 1$. The step function intervention model is formed as follows:

$$\begin{aligned} Z_t &= 1.9815 Z_{t-1} - 0.963 Z_{t-2} - 0{,}0185 Z_{t-3} + 5{,}6582 \times 10^{-15} Z_{t-4} - 37{,}484 S_t{}^{(62)} + 74{,}275 S_{t-1}{}^{(62)} \\ &\quad - 36{,}097 S_{t-2}{}^{(62)} - 0{,}6935 S_{t-3}{}^{(62)} + e_t + 1{,}0000 e_{t-1} - 3{,}0585 \times 10^{-13} e_{t-2} \end{aligned}$$

$$\text{with, } I_t = S_t{}^{(62)} = \begin{cases} 0, t < 62 \\ 1, t \geq 62 \end{cases}$$

With prediction accuracy using Mean Absolute Percentage Error (MAPE) of 1.9404% < 20%, the forecasting value of the IDX30 stock index in 2023, which ranges from Rp. 488 to Rp. 505 shows excellent forecasting results from the intervention model, which are very good.

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