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ARIMA Time Series Modeling with the Addition of Intervention and Outlier Factors on Inflation Rate in Indonesia

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ABSTRACT

Extreme events in a time series model can be detected when the precise timing of the event, known as the intervention, is known. When the exact timing of an event is unknown, it is referred to as an outlier. If these factors are neglected, the model's accuracy will be affected. To overcome this situation, it is possible to add the intervention or outlier factor into the time series model. This study proposes the combination of intervention and outlier analysis in time series models, especially ARIMA. It is intended to minimize the residuals and increase the accuracy of the model so that it is suitable for forecasting. Using the data of inflation rate in Indonesia, the conflict between Russia and Ukraine was used as an intervention factor in this case. Pre-intervention data (before February 2022) is used to construct the ARIMA model (1st model). After that, the modeling process continued by adding the intervention factor to the ARIMA model. The effect caused by the intervention allows an outlier to appear, so the process is continued by adding the outlier factor, called an additive outlier(AO) and innovative outlier (IO), into the model before (2nd model). The MAPE for the first and second models is 8.26% and 7.44%, respectively. The finding of this research shows that the ARIMA model with intervention and outlier factors, named as the 2nd model, is the best model. This study shows that combining the intervention and outlier factors into ARIMA model can improve the accuracy. The forecasting of the inflation rate in Indonesia for one period ahead in 2023 is in the range of 2.06%.

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A. INTRODUCTION

The ARIMA model, developed by Box and Jenkins in the 1960s, is one of the many types of time series techniques frequently used for forecasting (Zhou et al., 2023). The ARIMA model is one of the short-term time series modelling options that can be used (Alghamdi et al., 2019). The ARIMA model is a univariate time series model that ignores independent variables and only depends on the dependent variable to generate fairly accurate short-term forecasts (Mohamed, 2020). However, time series models such as this one might show limitations when dealt with with disturbances, such as noise, that result in significant fluctuations in the data (Elseidi, 2023). The occurrence of shock, characterised by noise, denotes the presence of an event known as intervention or outlier (Hasan, 2019).

In terms of time series modeling, the identification of extreme values, also known as outliers, can be identified to the influence of an event referred to as an intervention (Apostol et al., 2021). The intervention, according to the study includes a range of factors, including government policies, natural disasters, wars, and other factors where the timing of the event is known precisely (Hossein, 2021). In the analysis of time series data, a model that disregards the intervention or outlier effect might produce large error values (Schaffer et al., 2021). Hence, in order to handle the situation mentioned previously, it is necessary to add intervention and outlier factors into the time series model, rather than neglecting them. In terms of time series modeling, it is possible to add only the intervention factor or just an outlier factor.

The conflict between Russia and Ukraine in February 2022 has an impact on the economic sectors over many countries (Balbaa et al., 2022). It led to the rise of prices in various commodities, which led to a corresponding rise in the inflation rate (Junaedi, 2022). Inflation is referred to as a gradual rise in the general price level of goods and services over a period of time (Islam, 2013). Following the occurrence of the conflict, many commodity prices increased, resulting in a significant increase in the inflation rate in Indonesia (Syahtaria, 2022).

The Indonesian Ministry of Finance has announced that inflation in Indonesia for the year 2022 greater than the government's target. The government's inflation goal is set at 3%, however, the observed inflation rate from January to September 2022 has exceeded this target, reaching 4.84%. The conflict between Russia and Ukraine has been identified as a primary cause, leading to a subsequent rise in inflation in other nations, including Indonesia. The rise in the inflation rate was characterised by an escalation in the cost of many primary commodities, including oil, gas, and wheat. Low and well-controlled inflation can help people keep their buying power (Yu, 2023). Unstable inflation causes challenges for businesses in terms of planning their activities, including production, investment, and pricing of goods and services (Nugraha et al., 2023). Hence, it is crucial to predict the inflation rate in order for society and the government to anticipate the increase of prices in various commodities. This study aims to combine intervention and outlier factors to be added to the ARIMA time series model. Without ignoring the intervention and outlier factors, it is expected to bring out the best model with good accuracy for forecasting. A related study by Mahkya & Anggraini (2020) determined that the model with intervention and outlier factors is the best one.

B. METHODS

This Study uses monthly data on inflation rate in Indonesia from 2018 until 2023 obtained from official website of Bank Indonesia. This research using ARIMA model with single input intervention and outlier added to the model.

1. Autoregressive Integrated Moving Average (ARIMA)

The Autoregressive Integrated Moving Average (ARIMA) model is a type of ARMA(p, q) model that includes a non-stationary assumption. This non-stationarity is solved by applying a differencing process, repeated d times, until the data meet the stationarity assumption (Moghimi et al., 2023). The model used to write as ARIMA(p, d, q) where p denotes the autoregressive process, d represents the number of differencing and q means the moving average process order (Mahia et al., 2019). The ARIMA(p, d, q) model can be expressed as

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

where $\phi_p(B) = (1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p)$ (ϕ_p is p- parameter for the autoregressive process); $\theta_q(B) = (1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q)$ (θ_q is q- parameter for moving average process); B is backshift operator; e_t is error at time t which normally distributed with zero mean and σ_e^2 variance ($e_t \sim N(0, \sigma_e^2)$; Y_t is the value of Y at time t. The process of time series modeling using an ARIMA involves a sequential three-step procedure (Awe et al., 2020).

1. The identification of models can be obtained through the sample Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots to identify the alternative process (AR, MA, ARMA).
2. The process of parameter estimation uses the likelihood method to estimate the parameters for a tentatively chosen model.
3. The process to check the diagnostic test by using the residual from the tentative model that had been obtained.

After getting through of this sequence of modeling, the final model can be used for the purpose of forecasting.

2. Intervention Analysis

In time series, it is common to find events for which the exact timing is known, called intervention (Lopez Bernal et al., 2018). There are typically two types of intervention variables, specifically the step function and the pulse function (Guimarães & da Silva, 2019). These variables have only the values 0 and 1 to represent the non-occurrence and the occurence of an intervention (Buckley et al., 2020). The step function is a representation of an intervention that takes place at time T and is assumed to have long-term (permanent) effects (Ilmiah & Oktora, 2021). The intervention at time T with a step function at time t ($S_t^{(T)}$) can be written as

$$S_t^{(T)} = \begin{cases} 0, & t < T \\ 1, & t \geq T \end{cases} \tag{2}$$

In addition, the pulse function represents a short-term (temporary) effect on the intervention at time T (Vadrevu et al., 2020). The intervention at time T with a pulse function at time t ($P_t^{(T)}$) can be written as

$$P_t^{(T)} = \begin{cases} 0, & t \neq T \\ 1, & t = T \end{cases} \tag{3}$$

Let Z_t denote a time series with a single intervention, the general model can be expressed as follows (Damian Adubisi et al., 2015).

$$Z_t = m_t + N_t \tag{4}$$

where Z_t is responses variable at time t; N_t is time series at time t with no assumption of intervention (ARIMA before intervention); and m_t is the effect of the intervention at time t. The permanent effect and gradual effect of intervention can be written respectively as (Dewi et al., 2023).

$$m_t = \begin{cases} \omega P_t^{(T)}, for\ pulse\ function \\ \omega S_t^{(T)}, for\ step\ function \end{cases} \quad \text{and} \quad m_t = \begin{cases} \dfrac{\omega B}{1-\delta B} P_t^{(T)}, for\ pulse\ function \\ \dfrac{\omega B}{1-\delta B} S_t^{(T)}, for\ step\ function \end{cases}$$

3. Outliers

In time series, there are some types of outliers, two of them namely Additive Outlier (AO) and Innovative Outlier (IO) (Maqsood et al., 2019). The Figure 1 illustrates the presence of the outliers.

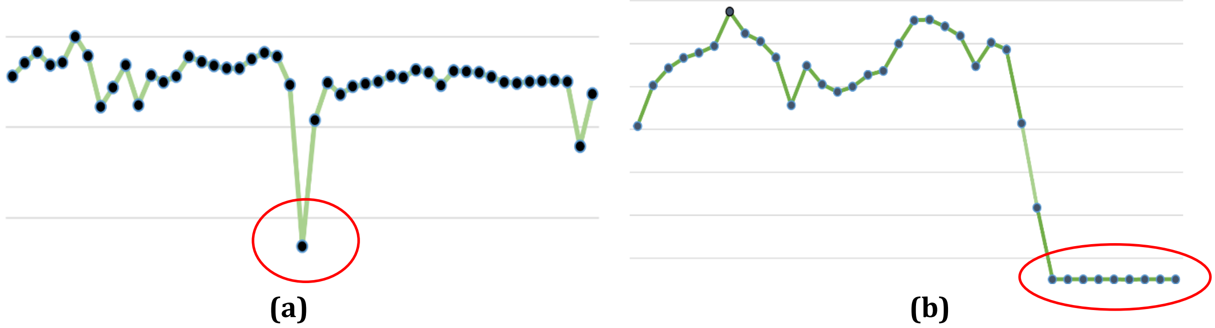

Figure 1. Types of outliers, (a) Additive Outlier, (b) Innovative Outlier

AO refers to an outlier that causes an impact only at a specific time point, denoted as T, with a value represented by ω (Huda et al., 2022). The model including AO (Z_t), can be written as follows

$$Z_t = Y_t + \omega I_t^{(T)} \tag{5}$$

where Y_t is an ARIMA model without outlier factor and $I_t^{(T)} = \begin{cases} 1, & t \neq T \\ 0, & t = T \end{cases}$. While IO gives impact to the entire observation, $Y_T, Y_{t+1}, \ldots$ beyond time T (Huda et al., 2020). The model with IO factor (Z_t) can be written as

$$Z_t = Y_t + \frac{\theta(B)}{\phi(B)} I_t^{(T)} \tag{6}$$

A general time series model that has more than one outlier can be expressed as (Mukhaiyar et al., 2019):

$$Z_t = \sum_{j=1}^{k} \omega_j v_j(B) I_t^{(T_j)} + Y_t \tag{7}$$

where Y_t is an ARIMA model without outlier factors; ω_j is j-outlier effect and

$$v_j(B) = \begin{cases} 1, & for\ AO \\ \dfrac{\theta(B)}{\phi(B)}, & for\ IO \end{cases}$$

Study research by Mukhaiyar et al. (2021) using outlier factors to be added into time series model and shows that ARIMA with outlier factor better than ARIMA without outlier factor.

4. Modeling Procedure

The research started its data analysis process by constructing an ARIMA model that used pre-intervention data. Following the selection of the best ARIMA model, the subsequent step meant adding the intervention factor into the ARIMA model before intervention. After that, the process is continued by checking the residual diagnostic test and detection outliers. The detection of outliers is conducted in cases where the ARIMA intervention model fails to fulfill the assumption of independent and normally distributed residuals (Laome et al., 2021). After combining the intervention and outlier factors to be added into ARIMA model, the final step is calculating the MAPE and forecasting. This modeling process is illustrated in Figure 2.

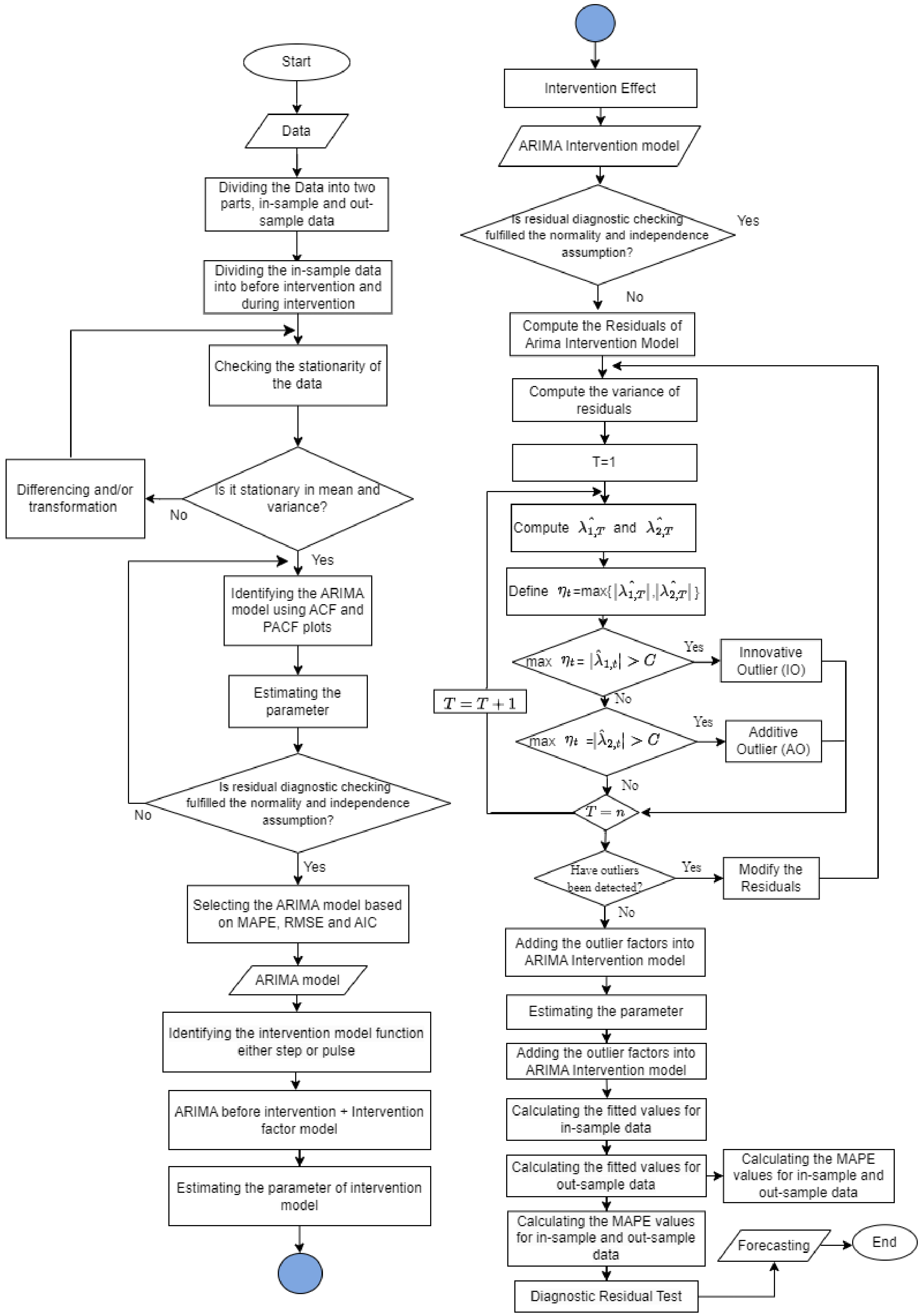

Figure 2. Flowchart of ARIMA modeling with Intervention and Outlier Factors

C. RESULT AND DISCUSSION

The data used for this research consists of the inflation rate monthly in Indonesia from January 2015 to September 2023, including a total of 105 observations. The data was sourced from the official website of Bank Indonesia. The data is divided into two parts, an in-sample dataset including 100 observations (January 2015-April 2023) used to construct and evaluate the model, while the remaining 5 observations is out-sample data (Mei-September 2023) used to evaluate the forecasting result. Figure 3 shows the data plot of and the boxplot of the inflation rate in Indonesia. The red bullet (February 2022) represents an intervention time in the event of a conflict between Russia and Ukraine.

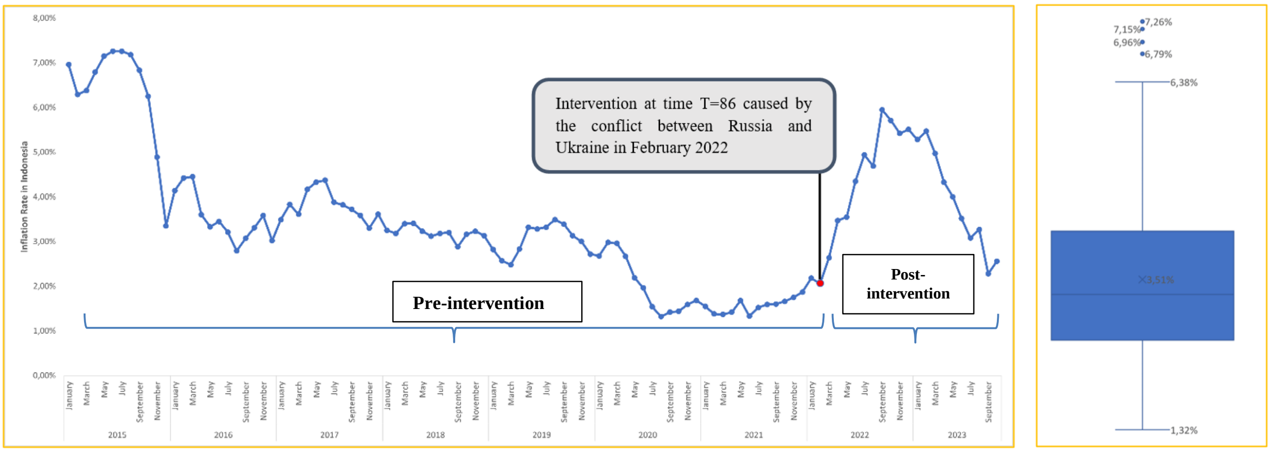

Figure 3. Inflation Rate in Indonesia Plot

Table 1. Descriptive Statistics for In-Sample Data

	Minimum	Maximum	Mean	Variance	Standard Deviation
Pre-Intervention	1.32	7.26	3.33	2.36	1.53
Post-Intervention	2.64	5.95	4.76	0.99	0.99

Since the intervention has occurred, Table 1 shows that the inflation rate in Indonesia has increased, indicating that the intervention has had an impact on inflation. Based on the boxplot in Figure 3, it can be seen there are 4 observations detected as the outliers. Furthermore, this can be an early indication of outlier factor in ARIMA time series model.

1. ARIMA Modelling before Intervention

The data utilized for constructing the ARIMA model consists of pre-intervention data. Before constructing the ARIMA model, it is required to assess the stationarity of the data in relation to both its mean and variance. The assessment of stationarity at the mean can be performed either through a visual inspection or by using the Augmented Dickey-Fuller (ADF) test. The ADF test result reveals the p-value used to assess stationarity at means, as displayed in Table 2.

Table 2. Stationarity Test at Mean

	p-value	Decision
Before differencing	0.117	Non-Stationary
1st Differencing	0.010	Stationary

Based on Table 2, the data is stationary at mean after the first differencing (d=1) when the p-value is below the 5% significance level. After that, the stationarity at variance can be evaluated using the rounded value (λ), and the result indicates that λ=1.13 which is closed to one. Resulting in that the data must be stationary at variance and means. Then, the utilisation of ACF and PACF plots for the purpose of identifying the ARIMA orders is illustrated in Figure 4.

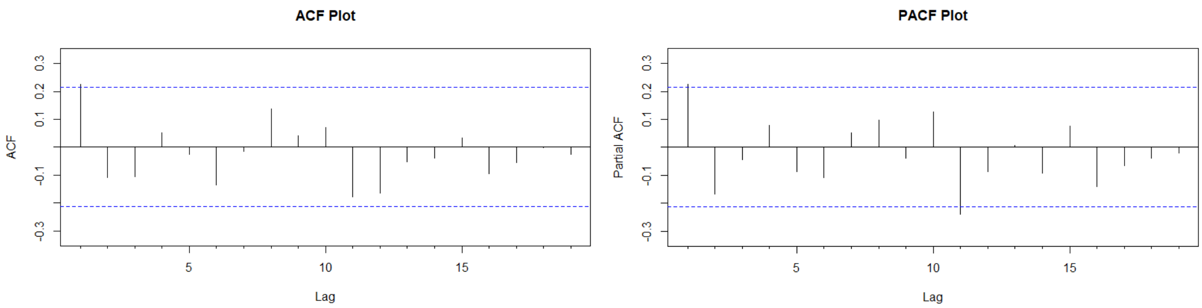

Figure 4. ACF and PACF Plots from Pre-Intervention Data

Based on Figure 4, the tentative ARIMA models before intervention are presented in Table 3. Following that, the initial models will be tested for residual diagnostics in order to verify the white noise assumption. The Ljung-Box test is used to fulfill the residual independence assumption, while the Shapiro test is used to examine the residual normality assumption, as shown in Table 3.

Table 3. ARIMA Tentative Models

			Model Accuracy			Residuals Diagnostic Test	
Model	**Parameter**		**AIC**	**MAPE**	**RMSE**	**Ljung-Box Test**	**Shapiro Test**
ARIMA(0,1,1)	θ_1	0.29	66.50	7.84%	0.34	0.61	0.0005
ARIMA(1,1,0)	ϕ_1	0.25	67.74	7.89%	0.35	0.46	0.0006
ARIMA(1,1,1)	θ_1	0.32	68.49	7.85%	0.34	0.52	0.0004
	ϕ_1	-0.03					

Table 3 shows the parameter estimation for all tentative models and the residual diagnostic test. From Table 3, all of the models fulfill the white noise assumption. Subsequently, the selection of the best model was determined by evaluating the criteria of the lowest values for AIC, MAPE, and RMSE. As a result, ARIMA(0,1,1) is the best model for ARIMA before intervention. The model of ARIMA after the parameter was estimated from Table 3 can be expressed based on equation (1) as

$$Y_t = Y_{t-1} - 0.29e_{t-1} + e_t \quad (8)$$

2. ARIMA Modelling with Intervention Factor

This study used the pulse function as an intervention factor, as it is predicted that the intervention has a temporary effect on the inflation rate in Indonesia. The intervention factor will be added into the ARIMA model that was obtained before in equation 8. The ARIMA + Intervention (T=86) model can be expressed in the form that follows.

$$Y_t = (1+\delta_1)Y_{t-1} - \delta_1 Y_{t-2} - (\theta_1+\delta_1)e_{t-1} + \delta_1\theta_1 e_{t-2} + \omega_1 P_t^{(86)} + e_t \quad (9)$$

After that, the parameter in equation (9) will be estimated which the results showed in Table 4.

Table 4. Parameter Estimation ARIMA(0,1,1) with Intervention Factor at T=86

Parameter	$\boldsymbol{\theta_1}$	$\boldsymbol{\omega_1}$	$\boldsymbol{\delta_1}$
Estimation Results	0.22	-0.48	0.56

So that the equation (9) can be written as

$$Y_t = 1.56Y_{t-1} - 0.56Y_{t-2} - 0.78e_{t-1} + 0.12e_{t-2} - 0.48P_t^{(86)} + e_t \quad (10)$$

where

$$P_t^{(86)} = \begin{cases} 1, & t = 86 \\ 0, & t \neq 86 \end{cases}$$

Figure 5 shows the effect of the intervention at time t

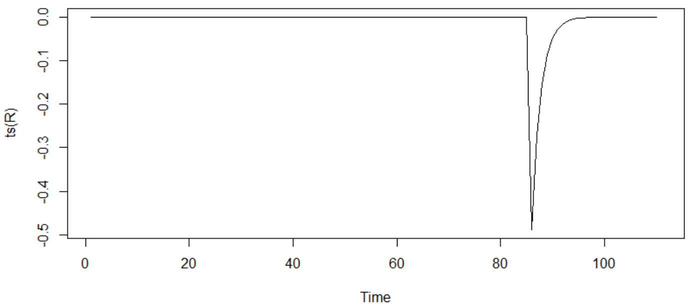

Figure 5. The Effect of The Intervention

The results found that the effect of the intervention shown in Figure 5 indicates a gradual decrease or convergence to zero. The analysis shows that the current war between Russia and Ukraine does not have a significant long-term effect on the inflation rate in Indonesia. Subsequently, the residual from the model (10) will be checked in diagnostic test (independency and normality of residual). The results show that the p-value for residual independence is 0.68 and p-value for residual normality is 0,001. The ARIMA model, which includes an intervention factor, fails to fulfill the assumption of normality. The issue is assumed to be caused by data outliers (Laome et al., 2021). Consequently, the process continues with the detection of the outlier based on the residual of ARIMA with intervention model.

3. ARIMA Modelling with Intervention and Outlier Factors

The identification of outliers using iterative process until no outlier detected (see Figure 2). The results indicate there are no more outlier detected until the 4th iteration. The outlier factors will be added to the previously obtained ARIMA intervention model. The ARIMA intervention model, which contains the addition of an outlier factors, can be expressed in the form that follows.

$$Y_t = (1+\delta_1)Y_{t-1} - \delta_1 Y_{t-2} - (\theta_1+\delta_1)e_{t-1} + \delta_1\theta_1 e_{t-2} + \omega P_t^{(86)} + \omega_1 I_t^{(11)} + \omega_2 I_t^{(12)} + \omega_3 I_t^{(93)} + \omega_4 I_t^{(13)} - \theta_1\omega_4 I_{t-1}^{(13)} + e_t \quad (11)$$

The process is continued by estimating the parameter at (11) which the results showed in Table 5.

Table 5. Parameter Estimation of ARIMA + Intervention + Outlier

Parameter	Type	Estimate
θ_1	MA(1)	0.11
ω	Intervention Parameter	-0.50
δ_1	Intervention Parameter	0.52
ω_1	Additive Outlier (T=11)	-1.24
ω_2	Additive Outlier (T=12)	-2.71
ω_3	Additive Outlier (T=93)	0.75
ω_4	Innovative Outlier (T=13)	-1.92

Based on Table 5, the equation in (11) will be written as follows

$$Y_t = 1.52Y_{t-1} - 0.52Y_{t-2} - 0.63e_{t-1} + 0.06e_{t-2} - 0.5P_t^{(86)} - 1.24I_t^{(11)} - 2.71I_t^{(12)} + 0.75I_t^{(93)} - 1.92I_t^{(13)} + 0.21I_{t-1}^{(13)} + e_t \quad (12)$$

where $P_t^{(86)} = \begin{cases}1, & t=86\\0, & t\neq 86\end{cases}$, $I_t^{(11)} = \begin{cases}1, & t=11\\0, & t\neq 11\end{cases}$, $I_t^{(12)} = \begin{cases}1, & t=12\\0, & t\neq 12\end{cases}$, $I_t^{(93)} = \begin{cases}1, & t=93\\0, & t\neq 93\end{cases}$, and $I_t^{(13)} = \begin{cases}1, & t=13\\0, & t\neq 13\end{cases}$

The final step is to check the obedience of the residual diagnostic test to the white noise assumption through the use of the Ljung-Box Test and Shapiro Test. The result that the p-value is 0.21 and 0.99, respectively which greater than 0.05 that implies the ARIMA (0,1,1) + Intervention(*T=86*) + Outlier factors satisfy the conditions of residual independence and normality. It also seems that adding the outlier factor can solve the problem related to the model's normality residual assumption.

4. Comparison and Prediction of The Models

The comparison of the ARIMA model and ARIMA model with intervention and outlier factors is shown in Table 6.

Table 6. Comparison of the Accuracy of Time Series Model

Model	In-Sample		
	MAPE	RMSE	AIC
ARIMA(0,1,1) [1st model]	8.26%	0.388	98.68
ARIMA(0,1,1)+Int(86)+AO(11,12,93)+IO(13) [2nd model]	7.44%	0.305	60.97

According to the results shown in Table 6, it can be seen that the ARIMA model, which consists of intervention and outlier factors, has the lowest levels of MAPE, RMSE, and AIC value. Before forecasting the inflation rate in Indonesia for one period ahead, model (12) was used to predict the out-of-sample data in order to evaluate the accuracy of the forecasting result based on constructed model. Based on the out-sample data, the model points out a MAPE of 35%, indicating a reasonable level of accuracy in forecasting the data. Figure 6 illustrates the comparison between the observed data (blue line) and the estimated values obtained from the time series model (orange line). It can be concluded that the fitted values have the same pattern as the actual data. The predicted inflation rate for Indonesia in the upcoming period of October 2023 will likely be within the range of 2.06%, as shown in Figure 6.

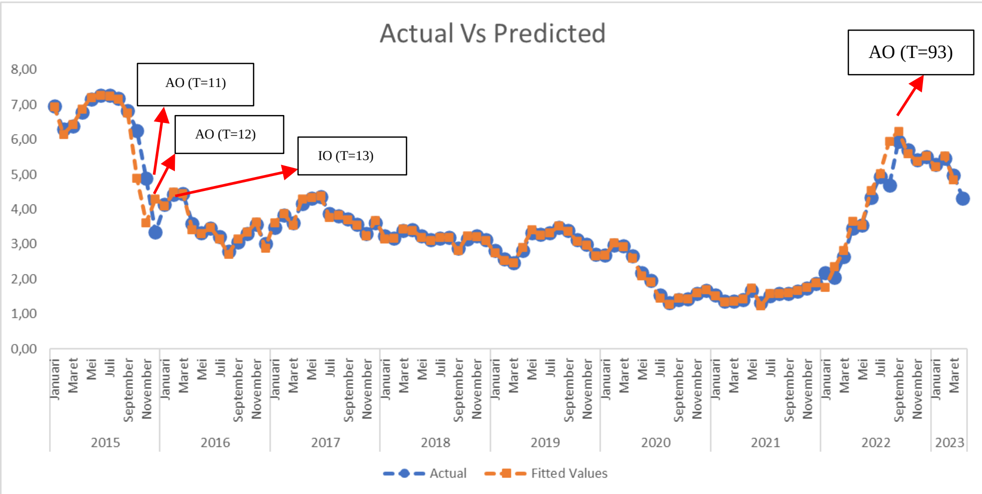

Figure 6. Actual vs Fitted Values of ARIMA Model with Intervention and Outlier Factors

D. CONCLUSION AND SUGGESTIONS

Based on the findings of the study, it can be concluded that the intervention in the conflict between Russia and Ukraine has had an effect of the increase on inflation rate in Indonesia, while its effect gradually decreases over the time. In addition to this, the occurrence of conflict between Russia and Ukraine has resulted in the identification of an extreme value as an outlier in the inflation rate of Indonesia. This study points out that combining intervention and outlier factors into the ARIMA model can enhance its accuracy compared to the ARIMA model without such factors. The projected inflation rate for October 2023 in Indonesia is in the range of 2.06%. This research is limited by only focusing on a single intervention with two type outliers to be added into ARIMA model. So, it is recommended to add more than one intervention factors (multi-intervention) in the further research.

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