

**MODELING OF WORLD CRUDE OIL PRICE BASED ON PULSE FUNCTION INTERVENTION ANALYSIS APPROACH**

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**DOI: 10.14710/medstat.16.2.136-147**

**Article Info:**

Received: 8 January 2023

Accepted: 27 December 2023

Available Online: 26 February 2024

**Keywords:**

*Crude Oil Price; Intervention Analysis; Pulse Function; Russia-Ukraine Geopolitical Conflict*

**Abstract:** Crude oil has important role in global economy, including Indonesia with considerable dependence on crude oil energy consumption. The increase in crude oil prices can be triggered by several factors, one of which is geopolitical conflict that occurred due to Russia's invasion of Ukraine on February 24, 2022. As the result, world crude oil prices rose above US\$100 per barrel for the first time since 2014. Therefore, this study uses pulse function intervention analysis approach to evaluate the impact of certain events in predicting data over the next few periods. The pulse function is used because the intervention occurs at the moment  $t$  only. The data used starts from June 8, 2020 to September 19, 2022 on weekly basis with the proportion of training and testing data is 90:10. The best intervention model obtained is ARIMA (3,2,0) with  $b=0$ ,  $s=1$ ,  $r=2$ , and intervention point at  $T=91$ . The prediction results for the next 12 periods obtained MAPE value of 2.8982% and MSE of 10.2687. This study is expected to help reduce risks due to uncertainty in world crude oil prices and in line with the goals of the Sustainable Development Goals (SDGs) to ensure access to reliable, sustainable, and affordable energy.

**1. INTRODUCTION**

Crude oil is currently a commodity that has crucial and dominant role in global economy because it is one of important inputs as energy source in production process (Joo et al., 2020). So, fluctuations in crude oil prices have important effect on macroeconomics and financial markets, including Indonesia. The increase in world crude oil prices can trigger an increase in Indonesia Crude Price (ICP). Indonesia is still importing oil and gas in large quantities to fulfill domestic fuel oil needs. Since 2004, Indonesia has switched to net oil importer from net oil exporter when Indonesia imported more crude oil than exported (Baek & Yoon, 2022). Central Bureau of Statistics (2022) also recorded Indonesia's imports of crude oil products from January to July 2022 which cumulatively reached US\$ 14.37 billion, this amount increased by 97.71% compared to the same period in 2021.

Several factors can affect the fluctuations international price of crude oil. Apart from demand and supply factors, it can occur due to non-fundamental factors such as geopolitical risk which are considered important factors affecting the security supply of crude oil (Wang et al., 2021). One of the geopolitical issues that is currently being global concern is Russia's invasion of Ukraine which resulted in rapidly increase of oil prices. The Russia-Ukraine

conflict indirectly affects the global economy because Russia is one of the largest energy exporters and oil producers in the world (Liadze et al., 2022). The Russian invasion of Ukraine that occurred on February 24, 2022 caused the price of crude oil to rise above US\$ 100 per barrel for the first time since 2014 (Finley & Krane, 2022). According to Ministry of Energy and Mineral Resources Republic of Indonesia (2022), the world oil prices increase also affected the ICP, which as of February 24, 2022 had reached US\$ 95.45 per barrel, while the ICP assumption in the 2022 state budget is only US\$ 63 per barrel.

One of the explanations related to the increase in crude oil prices can be done by building modeling and making predictions. Accurate modeling and prediction of the characteristics of crude oil is very important theoretically and practically to prevent and reduce market risk of traded assets due to uncertainty in the energy market, maintain the development of a healthy capital market, to encourage an increase in the Energy Consumption Structure (ECS) which concerned to the proportion of energy use (Liang et al., 2020). The most frequently used modeling method for time series data is the Autoregressive Integrated Moving Average (ARIMA). However, in time series data, it is not uncommon to find phenomena that cause changes in data patterns within a certain time, so that for special events, the classical ARIMA model is no longer appropriate. Therefore, intervention analysis is used to evaluate the impact of certain events in time series analysis.

Several previous studies have been conducted to model and predict crude oil prices, one of which has been done by He (2018) and Haque & Shaik (2021). Other previous studies that used pulse function intervention analysis in modeling and prediction was carried out by Min et al. (2011) and Wiri & Tuanah (2019). Based on previous researches, the novelty of this research is the use of intervention analysis on world crude oil prices that is currently a worldwide topic, namely the Russia-Ukraine conflict. The research that specifically models and predicts crude oil prices due to the Russian invasion of Ukraine uses intervention analysis that has never been done before. In addition, this study uses model accuracy and selection criteria that has proven to be accurate and widely used from previous research, namely Akaike's Information Criterion (AIC), Schwartz Bayesian Criterion (SBC), Mean Absolute Percentage Error (MAPE), and Mean Square Error (MSE).

The urgency of this research is the impact of the geopolitical conflict between Russia and Ukraine which has an impact on the global economy, one of which causes the increase of crude oil prices. In addition, this research is in line with the 7<sup>th</sup> point of the Sustainable Development Goals (SDGs), namely ensuring access to reliable, sustainable, modern, and affordable energy. The results of this research are expected to help many parties, from the public, practitioners, and government in anticipating and reducing risks due to uncertainty in crude oil prices. Thus, the security supply for crude oil commodities and global economic problems affected by the increase in crude oil prices can be handled better.

## **2. LITERATURE REVIEW**

### **2.1. Autoregressive Integrated Moving Average (ARIMA)**

Autoregressive Integrated Moving Average (ARIMA) is a time series analysis that identifies patterns in historical data to predict future data. There are three components, each of which helps to model certain types of patterns in the ARIMA model, namely Autoregressive (AR), Moving Average (MA), and Integrative (I) components. Based on these components,  $p, d, q$  order non-seasonal ARIMA model or ARIMA ( $p, d, q$ ) can be formed with  $p$  and  $q$  respectively indicate the order of the AR and MA processes, while  $d$  is the differencing order. Differencing operators can modify ARIMA ( $p, d, q$ ) models so that

the stationary condition can be fulfilled. ARIMA ( $p, d, q$ ) non-seasonal model based on Box et al. (2016) formulated as:

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

where  $(1 - B)^d$  is the operator for non-seasonal differencing ( $d$ );  $\phi_p(B) = (1 - \phi_1 B - \phi_1 B^2 - \dots - \phi_p B^p)$  is AR ( $p$ ) polynomial;  $\theta_q(B) = (1 - \theta_1 B - \theta_1 B^2 - \dots - \theta_p B^p)$  is MA ( $q$ ) polynomial.

Time series analysis requires data stationarity, which means that the properties underlying the process are not affected by time or the process is in balance. Non-stationary data can be converted into stationary data by transforming the data through the Tukey transformation. This step is carried out in order to obtain constant or stable variance, mean, and covariance conditions with the following transformation formula:

$$Z_t^{(\lambda)} = \begin{cases} Z_t^\lambda, \lambda \neq 0 \\ \ln Z_t, \lambda = 0 \end{cases} \quad (2)$$

where  $\lambda$  is transformation parameter or rounded value from Box-Cox transformation that can be estimated from the data which can make the data closer to a normal distribution.

There are several formal tests that can be used to determine stationarity conditions in the average of a time series. One test that is commonly used is the Augmented Dickey-Fuller (ADF) Test to assess whether a unit root is present in a time series, indicating non-stationarity. The ADF test is commonly represented by the regression equation:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \delta_2 \Delta y_{t-2} + \dots + \delta_{p-1} \Delta y_{t-(p-1)} + \varepsilon_t \quad (3)$$

where  $\Delta y_t$  is first difference of the original series;  $t$  is time;  $\alpha$  is constant term;  $\beta$  is coefficient on time;  $\gamma$  is coefficient on the lagged level of the series ( $y_{t-1}$ );  $\delta_1, \delta_2, \dots, \delta_{p-1}$  are coefficients on lagged first series differences  $\Delta y_{t-1}, \Delta y_{t-2}, \dots, \Delta y_{t-(p-1)}$ ; and  $\varepsilon_t$  is error term.

In addition, the ACF and PACF plots can indicate that the data has not fulfilled the stationary condition in mean. The data is not stationary in mean if the significance of ACF or PACF plots decays very slowly and differencing process must be applied after transformation process (Purwa et al., 2020). The basic idea of differencing is to subtract the  $Z_t$  observations from the previous observations  $Z_{t-1}$  (Cryer & Chan, 2008). When the data fulfilled stationary conditions in mean and variance, model identification can be reach out using ACF and PACF plots to determine the ARIMA order. Then, the process is continued with model estimation using Maximum Likelihood Estimation (MLE). After the significance requirements for the parameters are fulfilled, the diagnostic examination using residual analysis is conducted to test whether the assumptions of white noise and normal distribution of residuals are fulfilled.

## 2.2. Model Accuracy and Selection Criteria

This study uses model accuracy and selection criteria, namely AIC and SBC based on Murari et al. (2019), MAPE based on Mardianto et al. (2021), and MSE based on Ahmar (2020) which is formulated as follows:

1. Mean Square Error (MSE)

$$MSE = \frac{\sum_{t=1}^n (Z_t - \hat{Z}_t)^2}{n} \quad (4)$$

where  $Z_t$  is actual data at time  $t$ ;  $\hat{Z}_t$  is predicted data at time  $t$ ;  $n$  is the number of observations.

2. Akaike's Information Criterion (AIC)

$$AIC = n \ln(MSE) + 2p \quad (5)$$

where  $MSE$  is mean square error of residual;  $p$  is the number of parameters in model

3. Schwartz Bayesian Criterion (SBC)

$$SBC = n \ln(MSE) + p \ln n \quad (6)$$

4. Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{Z_t - \hat{Z}_t}{Z_t} \right| \times 100\% \quad (7)$$

The interpretation of the MAPE values for prediction accuracy based on Trimono et al. (2020) is presented in Table 1.

**Table 1.** The Interpretation of MAPE

MAPE Value	Interpretation
MAPE < 10%	Highly accurate
10 ≤ MAPE < 20%	Good
21 ≤ MAPE < 50%	Reasonable
MAPE ≥ 50%	Inaccurate

### 2.3. Intervention Analysis

Intervention analysis is time series analysis used to evaluate the impact of certain events, such as holidays, advertising promotions, to policy changes that affect data patterns. The intervention variable is only given a value of 1 or 0 which indicates whether or not the event is present in the data. According to Wei (2006), in general, there are two types of intervention variables, namely step and pulse. Intervention events that occur from time  $T$  onwards in a long time are called step functions which mathematically denoted as Equation 8.

$$I_t^{(T)} = S_t^{(T)} = \begin{cases} 0, & t < T \\ 1, & t \geq T \end{cases} \quad (8)$$

Meanwhile, the pulse function is defined as intervention event that only occurs at time  $T$  and doesn't continue at later time which mathematically denoted as Equation 9.

$$I_t^{(T)} = P_t^{(T)} = \begin{cases} 0, & t \neq T \\ 1, & t = T \end{cases} \quad (9)$$

The general form of the intervention model formulated as Equation 10.

$$Z_t = \frac{\omega_s(B)B^b}{\delta_r(B)} I_t^{(T)} + N_t \quad (10)$$

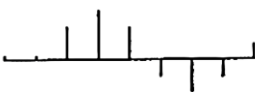
Where  $Z_t$  is response variable at  $t$ ;  $I_t$  is intervention variable;  $b$  is time delay from the effect of intervention  $I$  on  $X$ ;  $s$  is the duration of an intervention affects the data after  $b$  period;  $r$  is the pattern of intervention effect after  $b + s$  period since intervention event at time  $T$ ;  $\omega_s$  is  $\omega_0 - \omega_1(B) - \dots - \omega_s B^s$ ;  $\delta_r$  is  $1 - \delta_1(B) - \dots - \delta_r B^r$ ; and  $N_t$  is ARIMA model without intervention effect which formulated as Equation 11.

$$N_t = \frac{\theta_q(B)}{\phi_p(B)(1-B)^d} a_t \quad (11)$$

Where  $a_t$  is noise without intervention effect.

The order  $b, r$ , and  $s$  in intervention model can be determined by identify cross-correlation plot between the actual post-intervention data and the predicted data from the pre-intervention ARIMA model. Order  $b$  is determined when the effect of the intervention begins to occur that can be seen from the lag that first appears. Order  $r$  shows the pattern of residuals, for  $r = 1$  the impulse response weights show exponential decay and for  $r = 2$  the impulse response weights show damped exponential or damped sine wave. Order  $s$  is the delay time so that the data returns to stability calculated from the time the intervention occurred (Wei, 2006). Order  $b, r$ , and  $s$  are then used to determine the transfer function that will be involved in creating the intervention model. The illustration of order  $b, r, s$  and its typical impulse weights from cross-correlation plot is shown in Table 2.

**Table 2.** Illustration of  $b, r, s$  and Typical Impulse Weights

$b, r, s$	Typical Impulse Weights
(2, 2, 1)	

### 3. MATERIAL AND METHOD

#### 3.1. Data

The data used in this study is weekly world crude oil price data from Finance Yahoo (2022) from June 8, 2020 to September 19, 2022. The data is divided into training and testing data. Training data is data used in modeling while testing data is data used to compare predicted results with actual data. The amount of training and testing data is divided based on the ratio of 90% and 10% (Azlan et al., 2020; Mehta et al., 2021; Namazian et al., 2018). Therefore, training data period in this study starts from June 8, 2020 to June 27, 2022 (108 data) and the testing data period starts from July 4, 2022 to September 19, 2022 (12 data).

#### 3.2. Analysis Procedure

Descriptive analysis of World Crude Oil Price

- (1) Exploring data through descriptive statistics.
- (2) Making time series plot of all the data, then choose the extreme variables that allow an intervention to occur.

ARIMA analysis of Pre-Intervention World Crude Oil Price

- (1) Dividing the data into pre-intervention data (June 8, 2020 – February 21, 2022) and post-intervention data (February 28, 2022 – June 27, 2022). The main reason of break time selection is Russian invasion of Ukraine occurred on February 24, 2022 caused the price of crude oil to rise above US\$ 100 per barrel for the first time since 2014.
- (2) Examine stationarity in variance and mean of pre-intervention world crude oil price data through plots of time series data, ACF, PACF, and ADF test.
- (3) Carry out the Tukey transformation and differencing process if the pre-intervention data does not meet the stationarity assumption in variance and mean.
- (4) Identify the presumption ARIMA model from stationary in mean pre-intervention data based on the ACF and PACF plots.
- (5) Estimating the parameters of the pre-intervention ARIMA model.
- (6) Perform diagnostic checking on the presumption ARIMA model, including parameter significance tests, residual normality tests, and residual white noise tests. The ARIMA model must meet all of the diagnostic checking assumptions.
- (7) Selecting the best ARIMA pre-intervention model based on the smallest MSE value.

- (8) Predicting on post-intervention data based on the best ARIMA model from pre-intervention data.

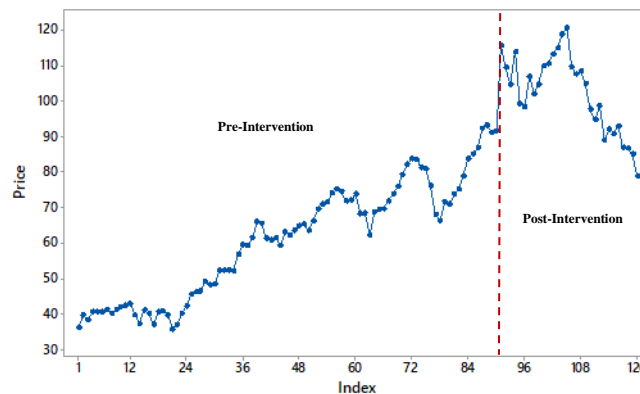
#### Modeling and Predicting World Crude Oil Price Based on Intervention Analysis

- (1) Plotting actual post-intervention data and the predicted results from the pre-intervention data to determine the order  $b$ ,  $r$ , and  $s$  on intervention model. The order of intervention was determined using Cross Correlation Function (CCF) plot. CCF is a useful measure for measuring the strength and direction of correlation between two random variables (Wei, 2006). CCF plots are often referred to as cross-correlograms.
- (2) Estimating the parameters of the intervention model.
- (3) Conducting diagnostic checking on the intervention model, including parameter significance tests, residual normality tests, and residual white noise tests. The intervention model must meet all of the diagnostic checking assumptions.
- (4) Selecting the best intervention model based on the smallest AIC and SBC values.
- (5) Predicting the data based on the selected intervention model. Modeling and predicting on intervention analysis using statistical software named Statistical Analysis System (SAS) (Cody, 2018).
- (6) Determine the prediction accuracy of the intervention model based on MAPE and MSE values.

## 4. RESULTS AND DISCUSSION

### 4.1. Descriptive Analysis of World Crude Oil Price

Descriptive analysis of world crude oil prices was carried out to find out price fluctuations from June 8, 2020 to September 19, 2022 on weekly basis. The time series plot of world crude oil prices is presented in Figure 1.



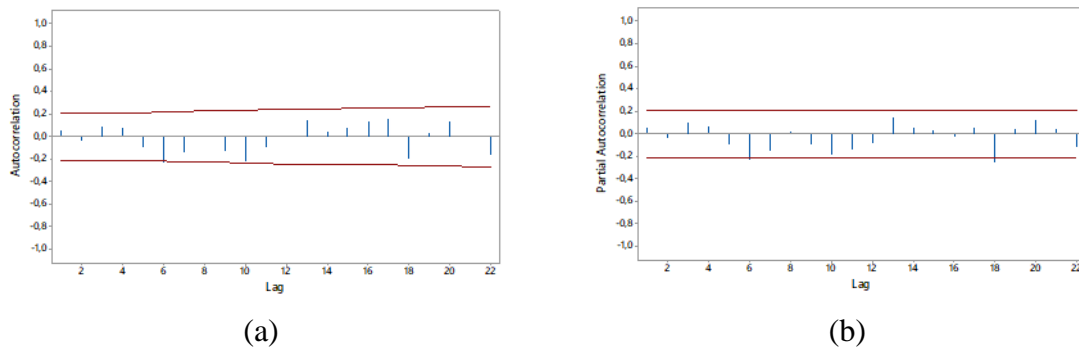
**Figure 1.** Time Series Plot of World Crude Oil Price

Figure 1 shows continuous increase in world crude oil prices until the highest increase occurred at  $t = 91$  on February 28, 2022 with prices reaching US\$ 115.68 per barrel. This increase occurred due to geopolitical conflicts resulting from Russia's invasion of Ukraine on February 24, 2022. As the result, world crude oil reached its highest price for the first time since 2014. This point then determined as the intervention point in the pulse function intervention analysis. The pulse function approach is chosen because the intervention occurs at the time  $T$ . Thus, the distribution of data before and after the intervention was obtained, that is at  $t = 1$  (8 June 2020) to  $t = 90$  (21 February 2022) as pre-intervention data, while  $t = 91$  (28 February 2022) to  $t = 120$  (19 September 2022) as post-intervention data.



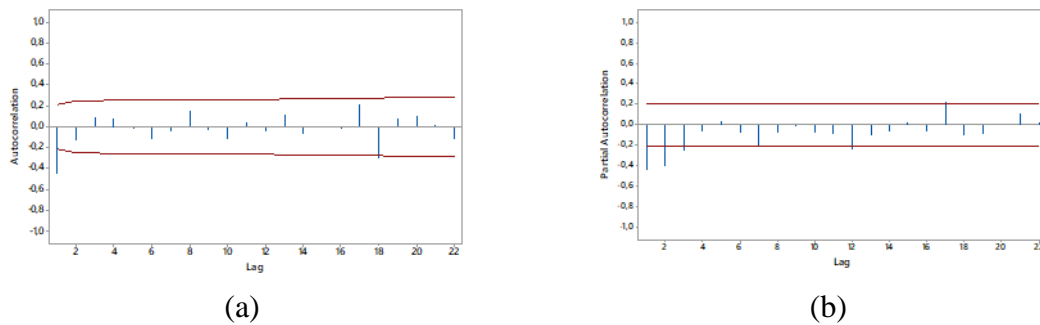
## 4.2. ARIMA Analysis of Pre-Intervention World Crude Oil Price

The first step taken before the intervention analysis was to conduct ARIMA modeling using pre-intervention data, from June 8, 2020 to February 21, 2022. The pre-intervention world crude oil price data in Figure 1 does not appear to be stationary because visually the mean and fluctuations are not constant. After conducting a formal test with ADF test, the data is not stationary in mean. Furthermore, based on Box-Cox plot, the data is not stationary in terms of variance because it produces a rounded value ( $\lambda$ ) of 0.5. Therefore, it is necessary to carry out transformation process using real data based on Equation (2). Then, differencing process using Box-Cox transformation data is carried out to stationary the data in mean. The ACF and PACF plots after the first differencing ( $d = 1$ ) are shown in Figure 2.



**Figure 2.** (a) ACF Plot (b) PACF Plot of World Crude Oil Price Pre-Intervention Data with  $d = 1$

Based on Figure 2, there is no significant lag so that the ARIMA model cannot be identified. Then a second differencing ( $d = 2$ ) is carried out which produces the ACF and PACF plots in Figure 3.



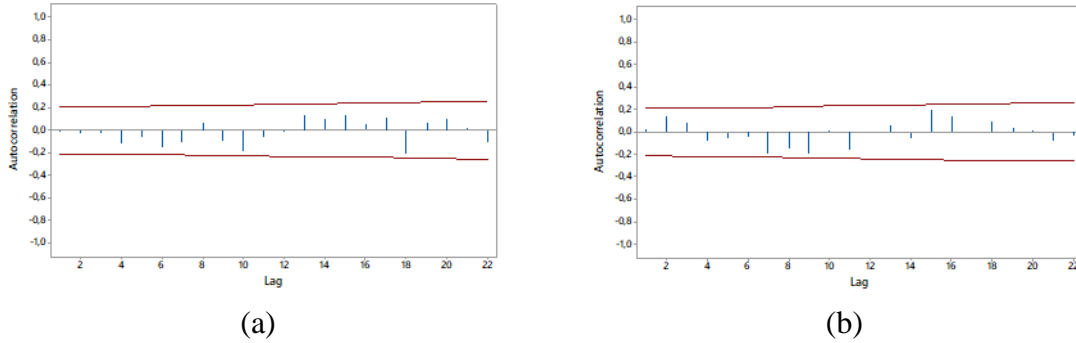
**Figure 3.** (a) ACF Plot (b) PACF Plot of World Crude Oil Price Pre-Intervention Data with  $d = 2$

Based on Figure 3, there is a significant 1st lag in the ACF plot and significant 1<sup>st</sup>, 2<sup>nd</sup>, and 3<sup>rd</sup> lags in the PACF plot. Therefore, some possible temporary ARIMA models for modeling pre-intervention world crude oil prices include ARIMA (1,2,0), ARIMA (2,2,0), ARIMA (3,2,0), ARIMA (0, 2,1), ARIMA (1,2,1), ARIMA (2,2,1), and ARIMA (3,2,1). Based on the estimation results, the model that meets the requirements for parameter significance is probabilistic ARIMA (3,2,0) with details in Table 3 below.

**Table 3.** ARIMA (3,2,0) Model Estimation Results

ARIMA	Model	Parameter	Estimate	P-value
(3,2,0)	Probabilistic	AR (1)	-0.746	0.00
		AR (2)	-0.582	0.00
		AR (3)	-0.278	0.01

Based on Table 3, ARIMA (3,2,0) model has fulfilled the parameter significance requirements because  $p\text{-value} < \alpha$  (0.05). The model also produces residuals that meet the white noise assumption and are normally distributed with MSE value of 0.0340. To show that the best ARIMA model is correct, not ARCH or GARCH model, conduct plot the ACF and PACF of residual and residual quadratic of ARIMA model with the results in Figure 4.



**Figure 4.** (a) Residual ACF Plot (b) Residual Quadratic ACF Plot

Based on Figure 4, it can be seen that the ACF plot has no lag that exceeds the limit. This supports that the pre-intervention ARIMA model that has been built is correct and there is no heteroscedasticity. The best model of pre-intervention ARIMA based on Equation (1) and the estimation results in Table 2 can be written as follows.

$$\phi_3(B)(1 - B)^2 \dot{Z}_t = \theta_0(B) a_t \quad (12)$$

$$(1 - \phi_1 B - \phi_2 B^2 - \phi_3 B^3)(1 - 2B + B^2) \dot{Z}_t = a_t \quad (13)$$

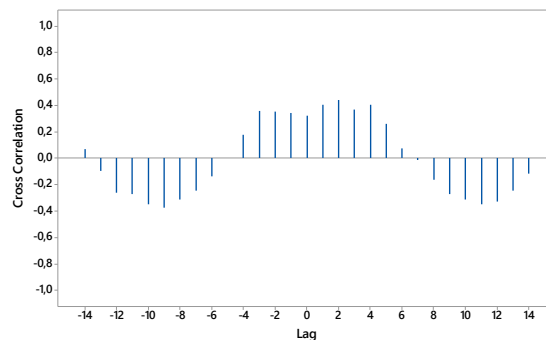
Equation (13) can be expressed in  $\dot{Z}_t$  as in Equation (14) as follows.

$$\begin{aligned} \dot{Z}_t &= \frac{a_t}{(1 - \phi_1 B - \phi_2 B^2 - \phi_3 B^3)(1 - 2B + B^2)} \\ \dot{Z}_t &= \frac{a_t}{(1 + 0.746B + 0.582B^2 + 0.278B^3)(1 - 2B + B^2)} \\ \dot{Z}_t &= \frac{a_t}{(1 - 1.254B + 0.09B^2 - 0.14B^3 + 0.026B^4 + 0.278B^5)} \end{aligned} \quad (14)$$

where  $\dot{Z}_t = \sqrt{Z_t}$

### 4.3. Modeling and Predicting World Crude Oil Price Based on Intervention Analysis

After obtaining the best ARIMA model from pre-intervention data, the next step is to plot cross-correlation on post-intervention training data with predictive data from pre-intervention ARIMA results to estimate the values of intervention parameters.



**Figure 5.** Cross Correlation Plot



The results of the plotting cross correlation in Figure 5 were then identified to see the intervention parameters  $b, s,$  and  $r$ . The intervention order  $b = 0$  because intervention effect began to occur at lag 0,  $s = 1$  because the delay time so that the data returned to stability was calculated from the time the occurrence of intervention is 1, and  $r = 2$  because there is sinusoidal pattern. After obtaining the order of intervention, then estimating the parameters of the pulse function intervention model and resulted estimation in Table 4.

**Table 4. Significance Test Result of Intervention Model**

Intervention Model	Parameter	Estimate	P-Value
ARIMA (3, 2, 0) with $b = 0, s = 1,$ $r = 2$	AR (1)	-0.6886	< 0.0001
	AR (2)	-0.5974	< 0.0001
	AR (3)	-0.2764	0.0052
	$\omega_0$	0.2117	< 0.0001
	$\omega_1$	-0.1499	0.0010
	$\delta_1$	-1.0691	< 0.0001
	$\delta_2$	-0.6866	< 0.0001

Based on Table 4, the intervention model has fulfilled the parameter significance requirements because  $p\text{-value} < \alpha (0.05)$ . In addition, the model produces residuals that meet the assumption of white noise and are normally distributed with AIC value of -329.203 and SBC value of -310.693. Therefore, this model can be used to predict world crude oil prices. The ARIMA (3,2,0) model with  $b = 0, s = 1, r = 2$  and the intervention point at  $T = 91$  based on Equation (10) and the estimation results in Table 4 are as follows.

$$\begin{aligned}
 Z_t &= \frac{\omega_1(B)B^0}{\delta_2(B)} P_t^{(91)} + \frac{\theta_0(B)}{\phi_3(B)(1-B)^2} a_t \\
 Z_t &= \frac{\omega_0 - \omega_1 B}{1 - \delta_1 B - \delta_2 B^2} P_t^{(91)} + \frac{a_t}{(1 - \phi_1 B - \phi_2 B^2 - \phi_3 B^3)(1 - 2B + B^2)} \\
 Z_t &= \frac{0.2117 + 0.1499B}{1 + 1.0691B + 0.6866B^2} P_t^{(91)} + \frac{a_t}{(1 + 0.6886B + 0.5974\phi_2 B^2 + 0.2764\phi_3 B^3)(1 - 2B + B^2)} \quad (15)
 \end{aligned}$$

From the results of the model that has been built in Equation (15), predicting will be carried out for the next 12 periods. The results of prediction and prediction accuracy based on MAPE and MSE are shown in Table 5.

**Table 5. Prediction Results and Accuracy of World Crude Oil Prices**

No	Date	Actual Data	Predicted Data	MAPE (%)	MSE
1	04/07/2022	104.79	104.5118	0.2662	0.0774
2	11/07/2022	97.59	100.8264	3.2099	10.4743
3	18/07/2022	94.7	99.0674	4.4085	19.0742
4	25/07/2022	98.62	96.8148	1.8646	3.2587
5	01/08/2022	89.01	94.3867	5.6965	28.9089
6	08/08/2022	92.09	91.7897	0.3272	0.0902
7	15/08/2022	90.77	89.595	1.3115	1.3806
8	22/08/2022	93.06	87.6542	6.1672	29.2227
9	29/08/2022	86.87	85.3022	1.8379	2.458
10	05/09/2022	86.79	83.1545	4.372	13.2169
11	12/09/2022	85.11	81.2556	4.7435	14.8564
12	19/09/2022	78.74	79.194	0.5733	0.2061
				2.8982	10.2687

Based on Table 5, the prediction results MAPE value of 2.8982% with a highly accurate interpretation of predictive ability based on Table 1 and MSE value is quite small with a value of 10.2687. Furthermore, the prediction for 10 periods after the testing data period are shown in Table 6.

**Table 6.** Prediction Results After Data Testing Period

No	Date	Actual Data	No	Date	Actual Data
1	26/09/2022	77.2387	6	31/10/2022	68.2038
2	03/10/2022	75.3693	7	07/11/2022	66.5531
3	10/10/2022	73.4937	8	14/11/2022	64.9034
4	17/10/2022	71.7078	9	21/11/2022	63.3073
5	24/10/2022	69.9374	10	28/11/2022	61.7627

## 5. CONCLUSION

The world crude oil price increase due to the Russia-Ukraine geopolitical conflict can be explained statistically through modeling and prediction through pulse function intervention analysis. The best intervention model obtained was ARIMA (3,2,0) with  $b = 0, s = 1, r = 2$  and the intervention point at  $T = 91$ . Furthermore, prediction for the next 12 periods result MAPE value is 2.8982% and the MSE is 10.2687. These results indicate that intervention analysis has a good ability in evaluating the impact of external events that affect extreme changes in trends in time series data.

The suggestion result from this research is the national energy dependence on oil and gas needs to be reduced by using alternative renewable energy sources, especially since Indonesia is still a net oil importer country. As the result, fluctuations in world crude oil prices greatly affect domestic oil prices. This effort is in line with Government Regulation No. 79 of 2014 concerning National Energy Policy with the target of renewable energy is 23% in 2025. For further research development, a longer data period can be used to evaluate the impact of Russian-Ukraine geopolitical conflict that is still happening.

## ACKNOWLEDGMENT

The authors would express the gratitude to Statistics Study Program, Faculty of Science and Technology, and Universitas Airlangga, also all parties who involved for support this research and publication.

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