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Analysis of Multi-Input ARIMA Interventions with Additive Outlier for Forecasting Price of Crude Oil West Texas Intermediate

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ABSTRACT

Crude oil derived from fossil fuels can be used as primary fuels, such as gasoline, and is the most important of the energy resources. Based on that, crude oil play a crucial role in the global economy movement because can be used as the main sources of energy all over the world. However, one of the benchmarks for crude oil from the USA is West Texas Intermediate (WTI). Known to produce high-quality oil, the price of crude oil of WTI fluctuates. In addition, fluctuations occur because of several factors, such as the availability of oil supplies, the embargo on oil imports, and the COVID-19 pandemic. The research aims to analyze price forecasting that occurs over the next five months and the accuracy level of the method used. The data that exists outliers is usually removed from forecasting that contains outliers, but that can affect the estimation result in the model. So, in this research intervention and outlier factors are added to the research to overcome the constraints In this study, the Multi-Input ARIMA Intervention and Additive Outlier (AO) method are used by modelling ARIMA pre-intervention. After that, the procedure is adding intervention and additive outlier with iterative procedures. Multi-Input ARIMA Intervention and Additive Outlier (AO) are used to determine the magnitude of fluctuations that occur. Data shocks causing outlier data can be used by adding AO factors. WTI oil price data was retrieved from investing.com with monthly data from January 2011 to June 2023. Based on the results of Multi-Input ARIMA intervention with Additive Outlier method, it has been determined that the movement of WTI oil prices in the next five months will increase compared to the last five periods of actual data. Because of incrased price of crude oil, it will impact of the economic growth all over the world. So, the government better controlled the price of crude oil at lower price. Multi-Input ARIMA interventions resulting in AIC, MAPE, and RMSE model each 941.490, 6.979%, and 5.913. So, Multi-Input and AO proven can be used to forecast data with fluctuate that data occur.

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A. INTRODUCTION

Crude oil, or petroleum is a liquid that has the characteristics of a blackish and thick texture composed of a combination of complex hydrocarbons containing nitrogen, oxygen, and sulfur with characterized by a thick texture and blackish color (Al-Dahhan & Shaymaa, 2019). According to research by Gupta & Nigam (2020), crude oil derived from fossil fuels can be used as primary fuels, such as gasoline, and is the most important of the energy resources. According to Ajnura & Juliansyah (2021) oil prices have an impact on economic growth all over the world. So, the benefits of crude oil play a crucial role in the global economy movement (Kayalar et al., 2017). The price of crude oil plays a crucial role in the economy because oil is one of the main sources of energy (Ajnura & Juliansyah, 2021). The world is abundant with scattered crude oil, but the West Texas Intermediate (WTI) is one of the main benchmarks for global crude price movement (Chen, 2022).

WTI crude comes from oil fields in the United States of Texas, Louisiana, and North Dakota. More commonly known as oil with "sweet" characteristics, WTI oil is composed of 0.24% sulfur, resulting in the oil having a low density and the oil that produced is light. Becaused of the oil of WTI that produced have low density and light oil causes the resulting crude oil of WTI is easily refined (Chen, 2022). Based on that, has a low density and generates products with high value (Azevedo et al., 2015). Because the oil produced by WTI is of high value, WTI has a high demand which affects the movement of oil prices (Chen, 2022). High demand of crude oil which can be affects the movement of oil prices (Chen, 2022).

In June 2014, the price of WTI oil rose to $105.37 per barrel (Mead & Stiger, 2015). The price of oil increases based on reports from the International Energy Agency (IEA) (2014) on the high demand for crude oil in the world caused by Russia and Ukraine, which are under political tension. Oil prices rose again in May 2022 due to the European Union's embargo on oil imports from Russia (Tan, 2022). Furthermore, according to IEA (2022), the price increases were based on the rising demand for oil fuel for jets approaching the summer driving season in the United States and Europe. The situation was exacerbated by a drop in the production of 1.5 million barrels of oil per day (BOPD) in the OPEC+ countries, leading to a rise in WTI oil prices (Wallance, 2022). Crude oil reached its lowest point in April 2020, coinciding with a worldwide lockdown that weakened the world economy (Le et al., 2021). On April 20, 2020, the world crude oil price fell by more than 90% (Le et al., 2021). This is because there is no demand for oil due to the lockdown and excessive oil production, so the price of oil dropped significantly below zero for the first time in history (Das et al., 2020).

Based on factors that occurred, the price of crude oil has fluctuated because of external and internal factors (Sustrisno et al., 2021). The price fluctuations of WTI oil are a very serious problem, given that oil is a vital commodity. According to the International Labour Organization (ILO) (2022), oil is primarily used by industry in generating electricity, running machines, and fuel for industrial distribution. Since WTI oil prices are fluctuating, it is necessary to predict the price of WTI. As for previous studies, the common prediction methods used are the Autoregressive Integrated Moving Average (ARIMA), exponential smoothing, and regression (Munarsih & Saluza, 2020). However, these methods are unable to make accurate predictions due to the extreme fluctuation of data (Lestari et al., 2022). In the WTI oil price data from January 2011 to June 2023, several incidents caused the price of oil to move fluctuatively, so the data indicated there were interventions and outliers. If data that fluctuated were not analyzed by adding intervention factors, then the major effect of an intervention on a time frame of data could not be known (Anjuita et al., 2023).

The data that exists outliers is usually removed from forecasting that contains outliers, but that can affect the estimation result in the model (Huda et al., 2022). As a result, if ARIMA, exponential smoothing, and regression methods that disregard intervention and outlier factors are used, then the interruption of intervention factors can be known and affect the estimation of the forecast. Intervention and outlier factors are added to the research to overcome the constraints of ARIMA, exponential smoothing, and regression methods.

This research is aim to forecast the 5 period of data on July until November 2023. More over, this research is to determine the accuracy of multi-input interventions ARIMA with AO in analysing WTI crude oil price forecasting with Multi-Input ARIMA interventions with AO. In the research carried out, there were several incidents in the data period January 2011 to June 2023 where WTI oil price moves fluctuated. If the fluctuating data is not analyzed by adding intervention factors and AO, then the effect of an intervention on a time series data cannot be known (Mukhaiyar et al., 2021). In forecasting conducted on time series data that contains outliers, the outlier data usually delete it can be affect on forecasting (Huda et al., 2022). Thus in this research are multi-input (there are more than two times of interventions) ARIMA intervention and Additive Outlier (AO) intervention to be a multi-input intervention is used.(Wiradinata et al., 2017).

B. METHODS

1. Autoregressive Integrated Moving Average (ARIMA)

In the models from time series data analysis, Autoregressive Integrated Moving Average (ARIMA) requires stationary data. The stationary required is divided into two, namely stationary in average ($\alpha < 0.05$) and stationary in variance ($\lambda = 1$). The general form of the ARIMA (p,d,q) equation is as follows (Box et al., 2016).

$$\phi_p(B)(1-B)^d \hat{Z}_t = \theta_0 + \theta_q(B) \tag{1}$$

where d is the differencing parameter, ϕ_p is the coefficient of AR of order p, θ_q is the coefficient of MA of order q, and B is the Backshift operator.

2. ARIMA Multi-Input Interventions

The ARIMA intervention method analyzes a specific event that causes a change in data patterns (Prabowo & Afandy, 2021). At the time before the occurrence of an event that can change the data pattern, the first step is to perform an analysis with the ARIMA method on pre-intervention data, whereas, on data that has changed data pattern, the analysis is continued using the previously obtained ARIMA model and added to the intervention factor. In intervention analysis, there are two types of interventions used, the step function $S_t^{(T)}$ and the pulse function $P_t^{(T)}$ (Wasani & Projo, 2022). The step function is an intervention that occurs at the-T time and the impact of the intervention can be felt continuously (Ray et al., 2014). On the step intervention that happen at T and the effect (ω) felt continuously, the effect at T and afterwards denote as 1.

Meanwhile, the pulse function is an intervention that occurs at the-T time, and the effect of intervention occurs only at a single time (Schaffer et al., 2021). The effect that occurs on pulse funtions only denote as 1 time that intervention happened on T. On the step and pulse interventions, with 0 and 1 value indicators are defined as non-occurrence and occurrence event effects of interventions (Adubisi et al., 2020). Both interventions can be defined as follows (Wiradinata et al., 2017).

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

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

In general, intervention effects are divided into permanent and gradual effects (Im'roah & Huda, 2021). The impact of an intervention that has a permanent effect, which b is the delayed start of the intervention. In step-function interventions, the permanent impact is (ω), which can be defined as $\omega B^b S_t^{(T)}$. The pulse function has a gradual effect and converges to zero, or in other words, the pulse function can be felt gradually and will end at a particular time can be written as $\frac{\omega B^b}{(1-\delta B)} P_t^{(T)}$. The general equation of ARIMA multi-input interventions is as follows (Ilmiah & Oktora, 2021).

$$Z_t = \sum_{j=1}^{k} \frac{\omega_j(B) B^{bj}}{\delta_j(B)} I_{jt} + N_t \tag{4}$$

with $\omega_j(B) = \omega_{J0} - \omega_{j1} B - \cdots - \omega_{js} B^s$ and $\delta_j(B) = 1 - \delta_{j1} B - \cdots - \delta_{jr} B^r$, I_{jt} is the variable of the intervention which can be a step or pulse function with $j = 1,2,\dots,k$. N_t is known as a noise series or noise model. We identify the noise model using data before the intervention (ARIMA pra intervention).

3. Outlier detection

Outliers are data from observations that move inconsistently in time series data (Huda et al., 2022). Additive outliers are effects that occur only at once in the-T observation (Huda et al., 2022). The iteration procedure is established to estimate data containing outliers. In AO outlier detection, an iterative procedure is used to predict the presence of time outliers that occur in the data. The process carried out in the AO iteration procedure is as follows (Box et al., 2016).

a. Calculate the residual $\hat{e}_t$ and the variance of the residual $\hat{\sigma}_e^2$

$$\hat{\sigma}_e^2 = \frac{1}{m} \sum_{t=1}^{m} \hat{e}_t \tag{5}$$

b. Calculating $\hat{\lambda}_t$. If $|\hat{\lambda}_t| > C$, then AO is detected at-T time

$$\hat{\lambda}_t = \frac{\omega_t}{\hat{\rho}\,\hat{\sigma}_e} = \frac{\hat{\rho}^2 \pi(B)\,\hat{e}_t}{\hat{\rho}\,\hat{\sigma}_e} \tag{6}$$

with $\hat{\rho}^2 = (1 + \hat{\pi}_1 + \cdots + \hat{\pi}_{n-t}^2)^{-1}$, $\pi(B) = \frac{\phi_p(B)}{\theta_q(B)}$, and $\pi(B)\,\hat{e}_t = (e_t - \pi_1 e_{t-1} - \cdots \pi_n e_{t-n})$

c. Modify the residuals at the time outliers are detected using Equation (7).

$$\check{e}_T = \hat{e}_T - \widehat{\omega}_T I_t^{(T)} \tag{7}$$

d. Recalculate $\hat{\lambda}_t$ using the residuals of the modified $\check{e}_t$ and $\hat{\sigma}_e^2$

e. Repeat the steps in the second process until the fourth process and the iteration process stops when the outliers are no longer identified.

After the time of outlier occurs obtained, the additive outlier model can be formed as follows (Ahmar et al., 2018).

$$Z_t = \frac{\theta(B)}{\phi(B)} a_t + \omega I_t^{(T)} \tag{8}$$

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

with the additive outlier indicator of variables defined as 0 and 1. The indicators of Additive Outlier, which denote non-occurrence and occurrence of outliers happened at-T time (Ahmar et al., 2018).

4. Modelling Procedure

The research started modelling ARIMA with pre-intervention data. Modelling ARIMA pre-intervention is used stationary in variance and mean data. After that, the next procedure adds the first intervention points ($j = j_1$) to the best model of ARIMA pre-intervention with passed of the residuals diagnostic test (Wiradinata et al., 2017). This method is illustrated in Figure 1.

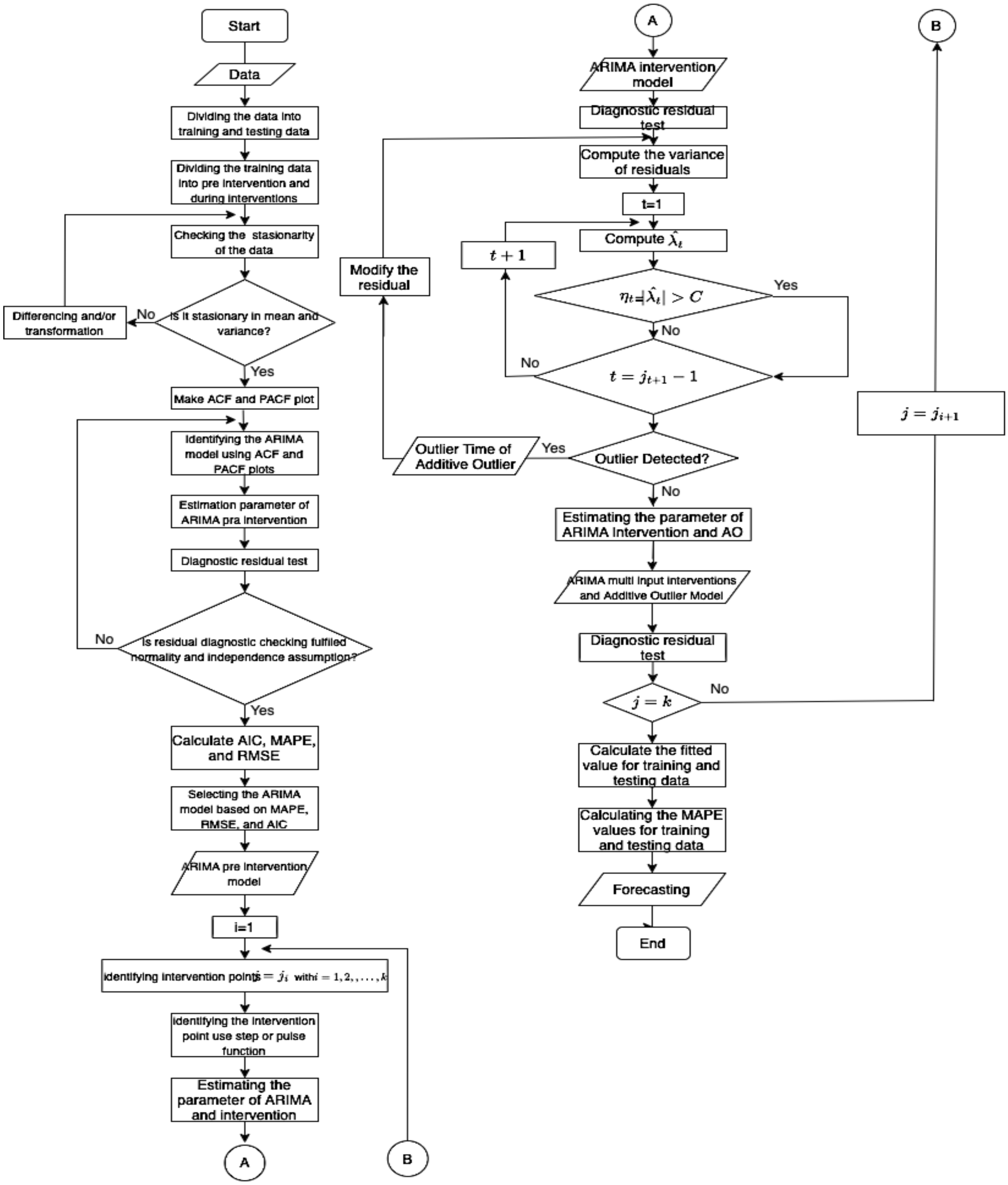


Figure 1. Flowchart of ARIMA Multi-Input Interventions with Additive Outlier

After that, the following process is detecting additive outlier. Usually, outliers existing in data modelling are removed or replaced with mean processes (Mukhaiyar et al., 2021). However, the outlier that exists in the data can be used in the forecast by adding additive outlier to the model (Mukhaiyar et al., 2021). So, the following process is adding the next interventions ($j = j_2$), and additive outlier are conducted with iterative procedures until the last intervention ($j = k$) and last data has been estimated. Then, after the model of ARIMA intervention multi-input with additive outlier obtained, the next step is calculating the MAPE and forecasting.

C. RESULT AND DISCUSSION

1. Descriptive Statistics

In 2014, the price of WTI oil experienced a change in the average pre-intervention data, from $96.781 down to $55.926 on average during intervention 1. This is because in the first intervention, there was an increase in world oil supply so that stocks were abundant and not accompanied by an increase in demand, so the influence of world crude oil prices decreased in intervention data 1. Table 1, which is descriptive statistics, and Figure 2, which is a plot of WTI oil price data for the period January 2011 to June 2023, are presented as shown in Figure 2.

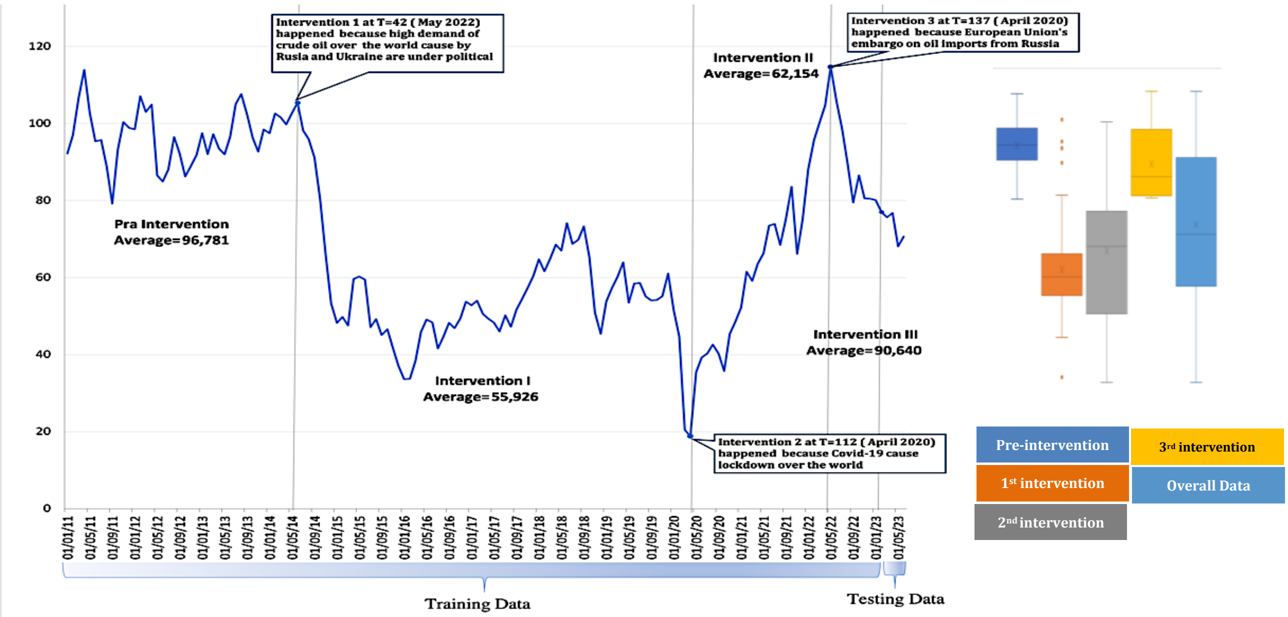


Figure 2. Price Crude Oil of WTI Plot

Figure 2 is illustrated the data that used in this research with the interventions points and the time that interventions happened on data. After that, in the Figure 2 illustrated the boxplot of data, on the 1^{st} intervention which can also be seen, there are several outliers in the first intervention. This is an initial detection that in the data used, there is a possibility that there are extreme changes in oil prices in the data used in the research**,** as shown in Table 1.

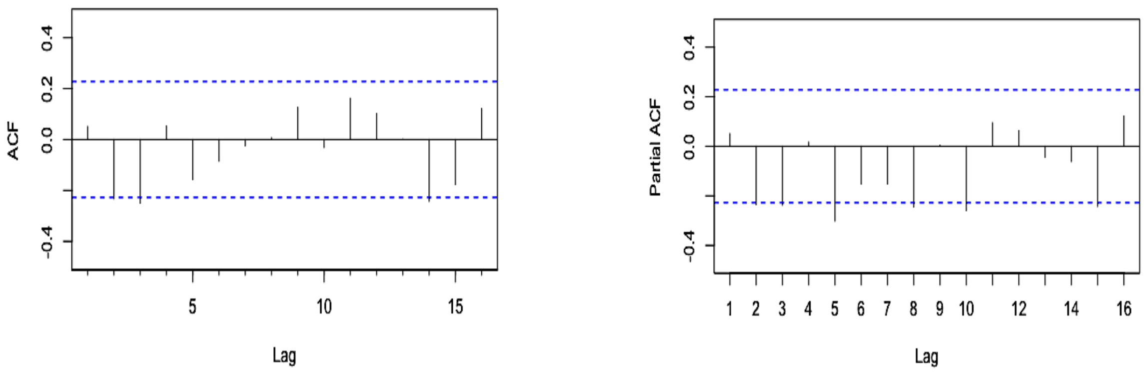
Table 1. Descriptive Statistic

	Average	Minimum	Maximum	Standard Deviation
Pre-Intervention	96.781	79.200	113.930	7.075
1^{st} intervention	55.926	20.480	105.370	14.514
2^{nd} intervention	62.154	18.840	104.690	22.294
3^{rd} intervention	90.640	79.490	114.670	12.884
Overall data	70.805	18.840	114.670	22.949

After that, in March 2015, there was a significant decline in the price of WTI crude oil due to an increase in the supply of crude oil, as quoted by the Ministry of Energy and Mineral Resources. In March 2020, there was another decline in the price of crude oil. This was due to COVID-19, which occurred and affected economic stability throughout the world. In the second intervention illustrated in Figure 2, the average price of crude oil again experienced a slight increase when compared to the previous intervention to \$ 62.154. This can be seen in March 2022, when the price of crude oil increased again, with the highest price in the second period of intervention, namely \$104.690. Some of the factors that caused crude oil prices to increase again when quoted from the Executive Summary are the political tension between Russia and Ukraine and infrastructure failures due to attacks and disasters that resulted in the paralysis of export facilities in Kazakhstan, causing reduced oil supply. After intervention 2, the average price of crude oil again experienced a drastic increase of \$ 90.640, with the highest price in oil prices occurring in May 2022 at \$ 114.670 due to the embargo carried out by the European Union against crude oil imports from Russia..

2. ARIMA Pre-Intervention

In the data modelling process, the first step is to model ARIMA on the pre-intervention data. ARIMA requires data that is stationary in variance and mean. Testing stationarity in variance, the rounded value (λ) obtained a value of 1.313, which is close to 1. This means that the pre-intervention data has been stationary in variance. Furthermore, after obtaining data that has been stationary in variance, it is continued by testing stationary in the mean on pre-intervention data. On the stationary in mean the oil price data needs to be differenced once ($d = 1$) to get data that is stationary in the mean. The p-value at the first differencing is $0.0419 < \alpha\ (0.05)$. So, the data has been stationary in variance and mean on the first differencing. Therefore, after obtaining data that are stationary in variance and mean, identification of the order of pre-intervention ARIMA can be done, as shown in Figure 3.



(a) (b)

Figure 3. Plot (a) Autocorrelation Function (ACF) and (b) Partial ACF (PACF)

Figure 3 shows a plot of ACF and PACF data from WTI oil data for the period 2011 to 2023. As for using the 85% confidence limit, it is found that there is an autocorrelation coefficient value and a partial autocorrelation coefficient that come out of the significant limit after lag 2. Using the parsimony principle, the possible models presented in Table 2.

Table 2. Parameter Estimation, Residual Diagnostic Test, and Model Accuracy

Model	Parameter		Residual Diagnostic Test		Model Accuracy		
			Ljung-Box	Shapiro Test	AIC	MAPE	RMSE
ARIMA (2,1,2)	ϕ_1	0.964	0.511	0.209	262.470	4.395	5.388
	ϕ_2	-0.415					
	θ_1	-1.214					
	θ_2	0.214					
ARIMA (0,1,2)	θ_1	-0.446	0.215	0.364	263.300	4.807	5.725
	θ_2	-0.554					
ARIMA (2,1,0)	ϕ_1	0.057	0.278	0.295	266.470	5.115	6.191
	ϕ_2	-0.241					

After obtaining the possible pre-intervention ARIMA model, parameter estimation, diagnostic tests, and selection of the best model are performed in Table 2. The selection of the best pre-intervention ARIMA model is based on the smallest AIC, MAPE, and RMSE values. In the residual diagnostic test, the three possible models passed the residual normality test and the residual independence test, so ARIMA (2,1,2) was chosen to be used in the pre-intervention ARIMA model based on the selection. The equation of ARIMA (2,1,2) can be written as:

$$Z_t = e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} + \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + Z_{t-1} - \phi_1 Z_{t-2} - \phi_2 Z_{t-3} \tag{9}$$

Thus, it can be concluded, after substituting the estimation parameter in Table 3, that the model of ARIMA (2,1,2) is as follows.

$$\begin{aligned} Z_t = e_t + 1.2141\, e_{t-1} - 0.2141\, e_{t-2} + 0.9643\, Z_{t-1} - 0.415\, Z_{t-2} + Z_{t-1} \\ - 0.9643\, Z_{t-2} + 0.415\, Z_{t-3} \end{aligned} \tag{10}$$

3. ARIMA Multi-Input Interventions and Additive Outlier

Next, the model of the pre-intervention ARIMA was augmented with intervention factors and outliers using an iterative procedure. The first intervention added to the model is the step function intervention factor because the perceived effect has a continuous effect. Meanwhile, in the second and third interventions, the intervention factor added to the equation is the pulse function intervention because the effect felt was only at that time, namely when COVID-19 and the EU oil import embargo against Russia occurred. The parameter estimates for the ARIMA intervention step function, as shown in Table 3.

Table 3. Parameters Estimation ARIMA Multi-Input Interventions and Additive Outlier

Iteration	Models	Parameters		Residual Diagnostic test		AIC	MAPE	RMSE
				Ljung-Box	Shapiro-test			
1st iteration	ARIMA (2,1,2) and step intervention	ϕ_1	-0.8944	0.962	0.030*	720.620	7.828	6.086
		ϕ_2	-0.1476					
		θ_1	1.1183					
		θ_2	0.4133					
		ω_{step1}	2.6904					
		ϕ_1	0.0105	0.666	0.347	709.190	6.802	5.727

Iteration	Models	Parameters		Residual Diagnostic test		AIC	MAPE	RMSE
				Ljung-Box	Shapiro-test			
2nd iteration	ARIMA (2,1,2), step intervention and Additive Outlier	ϕ_2	-0.4895					
		θ_1	0.1703					
		θ_2	0.4628					
		$\omega_{outlier}$	-23.317					
		ω_{step1}	3.3698					
3rd iteration	ARIMA (2,1,2), step and pulse intervention with Additive Outlier	ϕ_1	0.0978	0.851	0.104	881.070	7.089	5.937
		ϕ_2	-0.1439					
		θ_1	0.0458					
		θ_2	0.0745					
		$\omega_{outlier}$	-23.546					
		ω_{step1}	2.9866					
		δ_{pulse2}	0.3228					
		ω_{pulse2}	-25.362					
4th iteration	ARIMA (2,1,2), step, pulse, and pulse intervention with Additive Outlier	ϕ_1	0.0895	0.735	0.259	941.490	6.979	5.913
		ϕ_2	-0.1070					
		θ_1	0.0433					
		θ_2	0.0505					
		$\omega_{outlier}$	-23.507					
		ω_{step1}	2.9872					
		δ_{pulse2}	0.3299					
		ω_{pulse2}	-25.188					
		δ_{pulse3}	0.5183					
		ω_{pulse3}	12.757					

Based on the iterations that have been done, 1st iteration before the additive outlier was added, the normality has not been fulfilled*. So, from 2nd iteration until the 4th iteration, the additive outlier was added to fulfill the diagnostic residuals. So, the multi-input ARIMA intervention model with Additive Outlier is as follows.

$$Z_t = \omega_{step1} S_t^{(T)} + \frac{\omega_{pulse2}}{(1-\delta_{pulse2}B)} P_t^{(T)} + \frac{\omega_{pulse3}}{(1-\delta_{pulse3}B)} P_t^{(T)} + \omega_{outlier} I_t^{(T)} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} + \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + Z_{t-1} - \phi_1 Z_{t-2} - \phi_2 Z_{t-3} \quad (11)$$

The following is the multi-input ARIMA intervention model with AO on Equation (11) that has been substituted in the fourth iteration parameter estimation presented in Table 3 it can be written as

$$Z_t = 2.987\, S_t^{(42)} - \frac{25.188}{(1-0.3299B)} P_t^{(112)} + \frac{12.757}{(1-0.5183B)} P_t^{(137)} - 23.507\, I_t^{(111)} + e_t - 0.0433 e_{t-1} - 0.0505 e_{t-2} + 0.0895 Z_{t-1} - 0.107\, Z_{t-2} + Z_{t-1} - 0.0895\, Z_{t-2} + 0.1070\, Z_{t-3} \quad (12)$$

In the resulting ARIMA multi-input and AO model forecasting oil prices at period-t, the step intervention affects oil price forecasting by \$2.987 at the 42nd time point onwards. In the second and third pulse interventions, forecasting affects oil prices only at points 112nd and 137th with each intervention affecting price movements by -\$25.188 and \$12.757. Meanwhile, Additive Outlier affects oil price forecasting at the 111th point by -\$23.507. The intervention is also illustrated in Figure 4 on the plot of interventions and Additive Outlier Effect

$$S_t^{(42)} = \begin{cases} 0, t < 42 \\ 1, t \geq 42 \end{cases}$$
$$P_t^{(112)} = \begin{cases} 0, t \neq 112 \\ 1, t = 112 \end{cases}$$
$$P_t^{(137)} = \begin{cases} 0, t \neq 137 \\ 1, t = 137 \end{cases}$$
$$I_t^{(111)} = \begin{cases} 0, t \neq 111 \\ 1, t = 111 \end{cases}$$

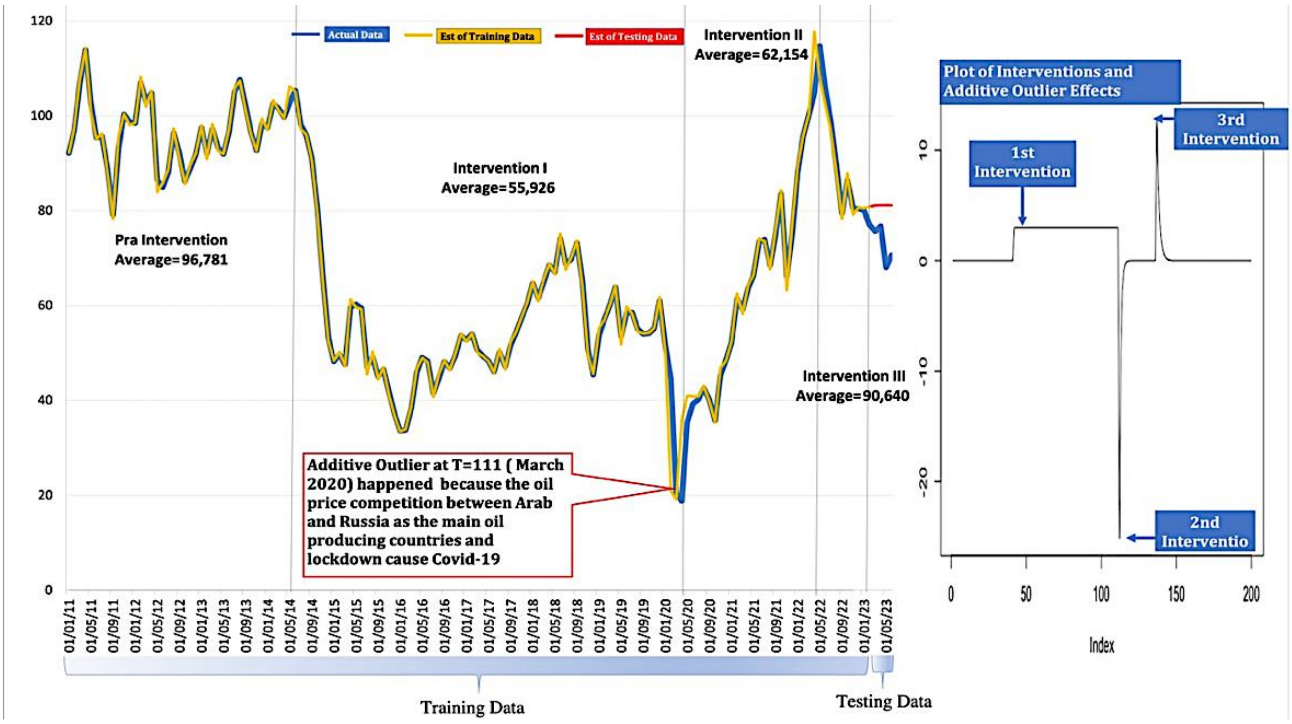


Figure 4. Fitted Value Data and Effect Plot

From the model obtained, illustrated in Figure 4, the fitted value plot of multi-input ARIMA interventions and additive outlier is very similar. It can be shown that the fitted value is identical because the fitted value data between the estimated and actual data has MAPE on the good category with values of MAPE on training and testing data, each 6.979% and 10.888%.

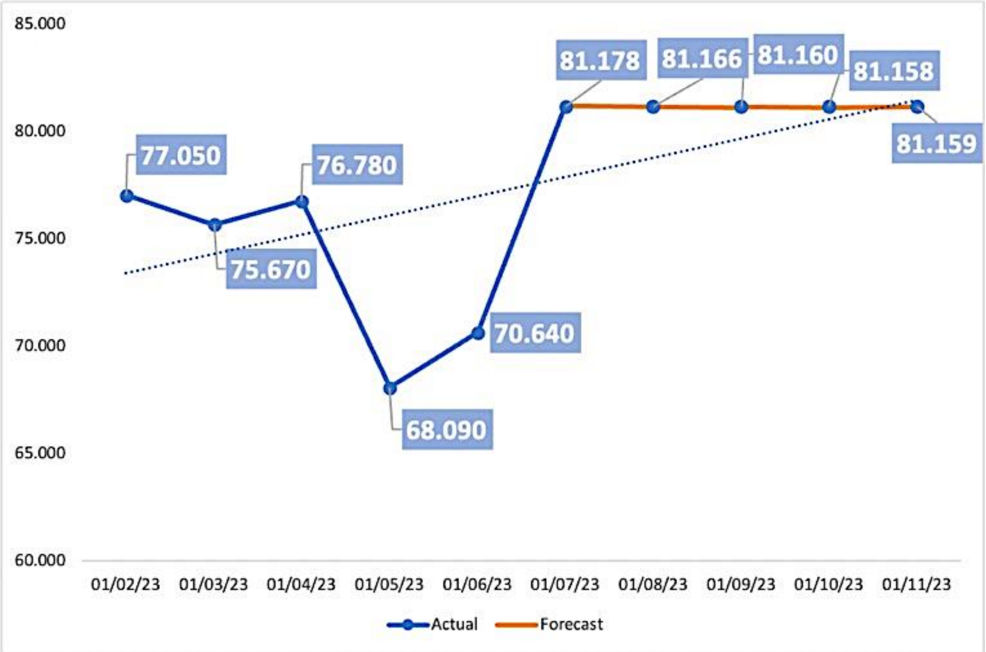


Figure 5. Trend of Forecasting Price of Crude Oil WTI VS Last 5 Periods of Actual Data

In Figure 5, it can be seen that the price movement has a positive trend when compared to five periods of actual data and forecasting data. However, the forecasting carried out for the next five periods using the multi-input ARIMA intervention method with AO shows that the price of WTI crude oil is expected to experience a decrease in price in 4 periods, namely from July to September, and improve again in November.

D. CONCLUSION AND SUGGESTIONS

Based on research conducted with the ARIMA multi-input intervention and Additive Outlier ARIMA using three intervention points, the forecasting results show that forecasting in the next five periods of WTI crude oil prices has increased in price when compared to five periods in actual data, namely in February to June 2023. Because of incrase price of crude oil, it will impact of the economic growth all over the world. So, the government better to controlled the price of crude oil at lower price. In the forecasting carried out, the forecasting model obtained using ARIMA (2,1,2) Multi-Input intervention with the addition of Additive Outliers shows the performance of the method used in the good category. This can be seen in the MAPE generated in the model using ARIMA multi-input intervention with outlier detection with MAPE training data and testing data of 6.979% and 10.888%. Based on the good category of method that used on this research, Multi-Input and Additive Outlier can be used to forecast data with fluctuate that data occur.

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