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OUTLIERS HANDLING ON SEASONAL ARIMA INTERVENTION MODEL (CASE: IMPACT OF MOST FAVORED NATION POLICY ON INDONESIAN HOT ROLLED COIL/PLATE)

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ABSTRACT

Intervention analysis measures the impact of various external events or interventions capable of changing data patterns. This research aims to determine the outliers handling on the seasonal ARIMA intervention model using the Box-Jenkins method. The pre-intervention model formed contains seasonal and step functions, which does not fulfill the white noise of the final intervention model. Therefore, outliers need to be detected so that the model meets the white noise assumption. The intervention model and outlier detection in this study are conducted to capture the impact of a tariff-setting policy of 5 and 15 percent, called the first and second intervention, on the volume of Hot Rolled Coil/Plate (HRC/P) imports. When the outlier is detected, the next step is to examine and adjust its effect on the model by adding the effect of the outlier in the model. Using the seasonal ARIMA intervention model, the results showed that the first and second interventions significantly reduced the volume of HRC/P imports. A limitation of this research is that this model cannot include other independent variables in the modeling.

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1. INTRODUCTION

Time-series data is often influenced by various activities referred to as interventions. According to [1], this consists of external events such as holidays, sales promotions, and policy changes. Its analysis is used to detect the initial impact of intervention when it occurs and the response form. This is divided into step and pulse functions. A step function is an intervention form that occurs at time T, or over a long period. Conversely, a pulse function occurs only at one time, T, or in a short period.

Modeling interventions is often inseparable from the interference caused by other external events, and its observation is called outliers [1]. The difference between an intervention and an outlier lies in the timing and cause of an event. Interestingly, assuming these are known, intervention analysis is used to measure the impact of an event, supposing the reverse is the case, then the detection of outliers is executed. Moreover, outlier detection also plays an essential role in forming intervention models because it causes assumption violations, such as nonstationary data, non-white noise model, and non-normality error. These also cause unreliable or even invalid inferences.

After the outlier is detected, the next step is to examine and adjust its effect on the model. In addition, [1] stated that it is useful for parameter estimation. Chen [3] further explained that the existence of outlier adjustments, by adding the effect of the outlier in the model, tend to cause previously insignificant intervention parameters to be significant. It also reduces the standard deviation value or residual variance, thereby increasing the t-values for parameter estimation and ensuring they become significant. This is because the reduction in residual variance with outliers is useful in checking models and obtaining better forecasting results.

Subsequently, [1] reported that some outliers are converted into relevant intervention variables due to some unknown policy changes, therefore, they are ignored during the early stages of data analysis. Instead of discarding the outlier effect, there is a need to incorporate certain information into the model by introducing appropriate response functions and intervention variables. This explicit form is useful in forecasting and controlling the univariate model based on outlier adjustment data. Chen and Liu [4] also reported that this adjustment is important for intervention analysis.

This research applies Hot Rolled Coil/Plate (HRC/P) as a steel product that is very popular in Indonesia because it can be applied for various things, for example general and welding construction, ship construction, pipes and tubes, automotive frame components, etc. This high need is not balanced by domestic production, resulting in a very high surge in imports. To overcome this problem, the government issued an intervention in the form of a policy of setting the Most Favored Nation (MFN) general import duty rate at 5 percent and followed by a policy of increasing the MFN general import duty rate by 15 percent. In this study, the existence of outliers was adopted in the modeling because it was indicated that in several periods there was an extreme decline, one of which was caused by the Covid-19 pandemic.

Based on the problem, this study aims to analyze the intervention model based on outlier adjustment using Indonesian hot-rolled coil or plate import volume from January 2009 to February 2021. The interventions include establishing or implementing the MFN general duty tariff policy of 5 percent and its increase by 15 percent. This is aimed to reduce the volume of HRC/P imports, which has increased since 2009.

2. RESEARCH METHODS

2.1 Data Source and Study Design

The data used is the Indonesian HRC/P import volume with the 7208 HS code, sourced from the Trade Ministry of the Republic of Indonesia. It was collected monthly data from January 2009 to February 2021. The pre-intervention period starts from the beginning of the study to the period before the first intervention (MFN tariffs of 5 percent), from January 2009 to December 2011. The first intervention period starts from when it first takes effect until the second intervention, from January 2012 to April 2015. The second intervention period starts from when it first takes effect (MFN tariff by 15 percent) until the end of the study period, covering May 2015 to February 2021, using the step function. This research generates the following hypothesis:

1. The policy of setting the Most Favored Nation (MFN) general import duty rate at 5 percent affects the volume of HRC/P imports
2. The policy of increasing the Most Favored Nation (MFN) general import duty rate by 15 percent affects the volume of HRC/P imports

2.2 Modeling process

Before an intervention model is developed, its initial form is called a pre-intervention. Furthermore, the model is an Autoregressive Integrated Moving Average (ARIMA), formed using the Box-Jenkins method, and this is divided into four stages, namely (i) model identification, (ii) estimation of parameters, and the selection of the best model based on the smallest AIC (Akaike's Information Criterion), SBC (Schwarz Information Criterion), and RMSE (Root Mean Square Error) criteria, (iii) model diagnostic test that includes error independence and normality error tests, and (iv) forecasting. The forecasting results are used to determine the intervention orders b, s, and r during the formation of the models, where b is the delay in starting the intervention, which is identified by the residual value that first goes out of bounds, s is the length of intervention affecting the data, and r is a pattern of interventional effects that occurs after (b+s) periods since the intervention at time T, r = 1 assuming the residual forms a pattern after (b+s) period and r = 0 when there is no pattern [1].

Occasionally, a time-series data indicates a seasonal pattern, therefore, a Seasonal Autoregressive Integrated Moving Average (SARIMA) model is formed. The stages of formation are identical to that of the ARIMA, developed using the Box-Jenkins method. However, the model identification stage is carried out using ACF and PACF examination in seasonal lag. For example, checks are carried out in patterns $r_4, r_8, r_{12,} r_{16}$, etc for quarterly data, while for that of monthly, it is rare to perform many autocorrelation checks for the lag in multiples of 12, therefore, they are carried out based on the available patterns, namely r_{12}, r_{24}, r_{36} [2].

Wei [1] stated that developing an intervention model starts with carrying out the variance stationarity test using box-cox and is defined as follows:

$$Y_t{}^{\lambda} = \begin{cases} \frac{Y_t{}^{\lambda}}{\lambda}, & \text{if } \lambda \neq 0 \\ \log(Y_i), & \text{if } \lambda = 0 \end{cases} \tag{1}$$

Y_t is a response variable or observed series, while λ (lambda) is a transformation parameter. Data is presumed to be stationary when the value of λ is equal to 1. Meanwhile, the data variance is not stationary when the value of $\lambda \neq 1$, then the box-cox transformation is stated as follows [1].

$$T(Y_t) = Y_t{}^{(\lambda)} = \frac{Y_t{}^{(\lambda)} - 1}{\lambda} \tag{2}$$

The average stationary analysis was performed using the Augmented Dickey-Fuller test (ADF test). Interestingly, when the data is not stationary, the differencing process is carried out until it becomes stationary. This indicates that the data is stationary at the first level or d-differencing. Mathematically, the equation is stated as follows

$$(1 - B)^{d-1}(1 - B)Y_t = \Delta^d Y_t \tag{3}$$

B is the back-shift operator. During the average stationarity examination, assuming the data indicates seasonal patterns, it becomes necessary to carry out differencing, which is further re-checked using the ADF-test. However, when the data is stationary against variance and average, the formation of a pre-intervention model using the Box-Jenkins procedure starts with (i) identification of the model through ACF and PACF patterns on the correlogram, (ii) perform the best parameter estimation and model selection while considering the smallest AIC, SBC, and RMSE values, (iii) perform model diagnostic analyses that include error independence and normality tests, and (iv) forecasting. The pre-intervention model formed is the ARIMA (p, d, q), where p is an order of autoregressive (AR), d is the degree of differentiation, and q is the order of the moving average (MA) [2], these are stated as follows.

$$Y_t = c + \emptyset_1 Y_{t-1} + \cdots + \emptyset_p Y_{t-p} + e_t - \theta_1 e_{t-1} - \cdots - \theta_q e_{t-q} \quad (4)$$

$\emptyset_i$ are autoregressive parameters, and θ_i are moving average parameters. However, assuming the data pattern is seasonal, the pre-intervention model formed is referred to as SARIMA reflected as ARIMA$(p, d, q)(P, D, Q)_s$, where P is an AR order for seasonal, D is differencing against seasonal, and Q is an MA ordering for seasonal. In general, the SARIMA model in the operator's backshift is stated as follows.

$$\Phi_P(B^s)\emptyset_p(B)(1-B)^d(1-B^s)^D Y_t = \mathrm{c} + \theta_q(B)\Theta_Q(B^s)e_t \quad (5)$$

$\emptyset_p(B)$ is nonseasonal order of autoregressive, $\Phi_P(B^s)$ is seasonal order of autoregressive, $\theta_q(B)$ is nonseasonal order of moving average, $\Theta_Q(B^s)$ is seasonal order of moving average. The pre-intervention model represents the noise aspect and is assumed to be invariant after estimating the intervention effect [5]. Once this phase is formed, an intervention model is established by determining its orders. The order of the first intervention is the difference between the original data realized from the first period and the results obtained from the forecasting of the pre-intervention model. Meanwhile, the second-order is determined from the difference between the original data of the second period and the forecasting results of the first intervention model. Wei [1] stated that the general form of the multi-input intervention model is stated as follows.

$$Y_t = \theta_0 + \sum_{j=1}^{k} \frac{\omega_{sj}(B)B^{bj}}{\delta_{rj}(B)} I_{jt} + \frac{\theta(B)}{\emptyset(B)} e_t \quad (6)$$

$\omega_s(B)$ is parameter of order b and s, $\delta_r(B)$ is parameter of order r. The formation of the intervention model is reported in detail by [1], [6]. According to [6], ARIMA Multivariate model (MARIMA) is an extension of the SARIMA Intervention model [7]. It consists of a pre-intervention SARIMA and intervention functions, thereby forming a multivariate model [8]. The SARIMA intervention model is stated as follows:

$$Y_t = \sum_{j=1}^{k} \frac{\omega_{sj}(B)B^{bj}}{\delta_{rj}(B)} I_{jt} + \frac{\Theta_Q(B^s)\theta(B)}{\Phi_P(B^s)\emptyset(B)} e_t \quad (7)$$

The impact is determined after the intervention model has been formed [9]. In addition, outliers are additional special cases perceived as part of the analysis. They consist of 4 types, and each has a different impact, which is stated as follows

1. Additive Outlier (AO) exhibits a single impact, and it does not affect other observations both before and after the outlier is located. The AO model is stated as follows

$$Y_t = \frac{\theta(B)}{\emptyset(B)} e_t + \omega I_t^{(T)}, \text{ where } I_t^{(T)} = \begin{cases} 1 & t \neq T \\ 0 & t = T \end{cases} \quad (8)$$

2. Where $\frac{\theta(B)}{\emptyset(B)} e_t$ is similar to the general ARMA (p,q), ω is the magnitude of the outlier effect, $I_t^{(T)}$ is the indicator variable representing the presence ($I_t^{(T)} = 1$) or absence ($I_t^{(T)} = 0$) of an outlier at time T.
3. Innovational Outlier (IO), the effect is similar to the ARMA process. Therefore, it affects the entire data series or observation. The IO model is stated as follows

$$Y_t = X_t + \frac{\theta(B)}{\emptyset(B)} \omega I_t^{(T)}, \text{ where } I_t^{(T)} = \begin{cases} 1 & t \geq T \\ 0 & t < T \end{cases} \quad (9)$$

Where X_t is the outlier-free series, $\frac{\theta(B)}{\emptyset(B)}\omega$ denotes the magnitude of the outlier effect, similar to the ARMA process.
4. Level Shift (LS) suddenly influences data series, thereby leading to a permanent change. The LS model is stated as follows

$$Y_t = X_t + \frac{1}{(1-B)} \omega_L I_t^{(T)}, \text{ where } I_t^{(T)} = \begin{cases} 1 & t \geq T \\ 0 & t < T \end{cases} \quad (10)$$

Where $\frac{1}{(1-B)}\omega_L$ denote the magnitude of the outlier effect.

5. Temporary Change (TC) produces an initial effect of ω at time t, which slowly reduces according to the magnitude of δ. The TC model is stated as follows

$$Y_t = X_t + \frac{1}{(1-\delta B)}\omega_c I_t^{(T)}, \text{ where } I_t^{(T)} = \begin{cases} 1 & t \geq T \\ 0 & t < T \end{cases} \tag{11}$$

Where ω indicates the magnitude of the outlier's impact that decreases gradually by δ, δ is a parameter designed to model the pace of the dynamic dampening effect. However, assuming δ =1, the outlier effect is the same as LS, and when δ = 0, it is the same as AO.

Adding outliers to the analysis is useful in discovering its causes and nature. Some are converted into several important intervention variables that strengthen the analysis related to changes in data patterns. In addition, the addition of outliers is useful for parameter estimation and is also used to check and forecast the model. A combination of intervention analysis and outlier detection is explicitly useful in forecasting and control than univariate models based on adjusted data. Several studies have investigated the combination of intervention analysis and outlier detection, including [4], [10]–[13].

Specifically, the processes of ARIMA intervention for this study are:

1. Divide the data into three groups, namely data from the pre-intervention period, data from the first intervention period, and data from the second intervention period. The first data period was from January 2009 to December 2011 or 36 data series (t = 36). The second data period was from January 2012 to April 2015 or 40 data series (t = 40). The third data period is from May 2015 to February 2021 or 70 series of data (t = 70).
2. Test stationarity of variance and mean. The stationarity of variance test was carried out using Box-Cox. When the data is not stationary in terms of variance, a Box-Cox transformation is carried out. The average stationarity test was carried out using a unit root test, namely the ADF-test. When the data is not stationary relative to the average, it is necessary to differentiate seasonality if the data pattern indicates a seasonal pattern.
3. Model formation before intervention. At this stage, model identification, parameter estimation, and error independence and error normality assumptions are tested. After obtaining several models from the correlogram, the best model is selected based on consideration of the smallest AIC, SBC and RMSE values. Then a model evaluation is carried out, namely a diagnostic test which includes testing the assumption of error independence (white noise) and error normality. After obtaining the best, forecasting is carried out to predict the value of the data for the first intervention period.
4. Identify the first order of intervention. The first intervention model was obtained from identifying the residual plot, which was obtained from the difference between the data for the first intervention period and the forecasting value of the model before the intervention. Identification of the first intervention ARIMA model from the residual plot that has been formed against $\pm$ 2 times the RMSE of the model before the intervention is used to determine the order of b, s, and r.
5. Parameter estimation, parameter significance, and evaluation of the first intervention model. After selecting the orders b, s, and r, model parameter estimation, parameter significance testing, and evaluation of the first intervention model were carried out through diagnostic tests of independence of error (white noise) and normality of error. Estimation of model parameters was carried out using the Least Square method. If the model meets these two assumptions tests, then the model is selected as the first intervention model and then forecasting is carried out to form the second intervention model.
6. Identify the second order of intervention. The formation of the second intervention model or final intervention is the same as the formation of the first intervention model, namely it is obtained from identifying residual plots obtained from the difference between the data for the second intervention period and the forecasting results of the first intervention model. Identification of the second intervention model from the residual plot that has been formed against $\pm$2 times the RMSE of the first intervention model is used to determine the order of b, s, and r.
7. Parameter estimation, parameter significance, and evaluation of the first intervention model. After selecting the orders b, s, and r, model parameter estimation, parameter significance testing, and evaluation of the second intervention model were carried out through diagnostic tests of independence

of error (white noise) and normality of error. Estimation of model parameters was carried out using the Least Square method. If the model meets these two assumptions tests, then the model is selected as the final intervention model.

8. Intervention model outlier detection. Outlier detection is carried out when no model meets the assumptions after a trial-and-error process. Outlier detection is carried out repeatedly and then one by one they are entered into the model with the first outlier added being the most significant outlier as indicated by the smallest Chi-Square probability value. The addition of outliers to the model is carried out until the model formed meets all assumptions.

9. Measuring the impact of interventions. Before calculating the magnitude of the impact of the intervention, it is necessary to return the data to its pre-transformation form, also known as data inversion. The impact of the intervention is obtained from the difference between the forecasting results of the final intervention model and the model before the intervention.

3. RESULTS AND DISCUSSION

3.1 Stationary test

The stationarity variance test carried out using box-cox showed that the HRC/P import volume data is not stationary because the value of λ (lambda) is not equal to 1 rather, it is 0.5. A transformation was carried out in the form of roots ($\sqrt{Y_t}$) and $\lambda = 1$. The subsequent step is the stationarity test on the average data realized from the pre-intervention period, which indicates a seasonal pattern. It is exhibited by a decrease in the volume of HRC/P imports that repeats itself in every 7th lag, thereby ensuring the execution of seasonal differencing.

The pre-intervention data obtained from the original series is not stationary at the level indicated by the t-value (-1.40), which is less than that of the critical at alpha = 5% (-2.95). Therefore, H_0 is accepted at all levels of significance. Meanwhile, the data obtained from seasonal differencing is stationary at the 5 percent significance levels as indicated by the t-value (-3.30), which is greater than that of the critical (-2.97). Therefore, H_0 is rejected at all levels of significance.

3.2 Pre-intervention Model

Based on previous stationarity tests, the pre-intervention model formed is the seasonal ARIMA (SARIMA), which was later converted to an intervention model. Several related studies have been carried out on this model, such as [7], [8], [14]. A model selection is used to obtain the best pre-intervention model based on the formed correlogram's smallest AIC, SBC, and RMSE values, as shown in Table 1.

Table 1. Pre-Intervention Model Candidates

ARIMA	AIC	SBC	RMSE
ARIMA $(1,0,1)(0,1,1)_7$	304.35	308.45	43.80
ARIMA $(0,0,1)(0,1,1)_7$	315.21	317.94	53.65
ARIMA $(1,0,0)(0,1,1)_7$	303.58	306.31	43.90
ARIMA $(1,0,1)(0,1,0)_7$	303.50	306.23	43.84
ARIMA $(0,0,1)(0,1,0)_7$	313.33	314.69	52.79
ARIMA $(1,0,0)(0,1,0)_7$	302.00	303.37	43.43

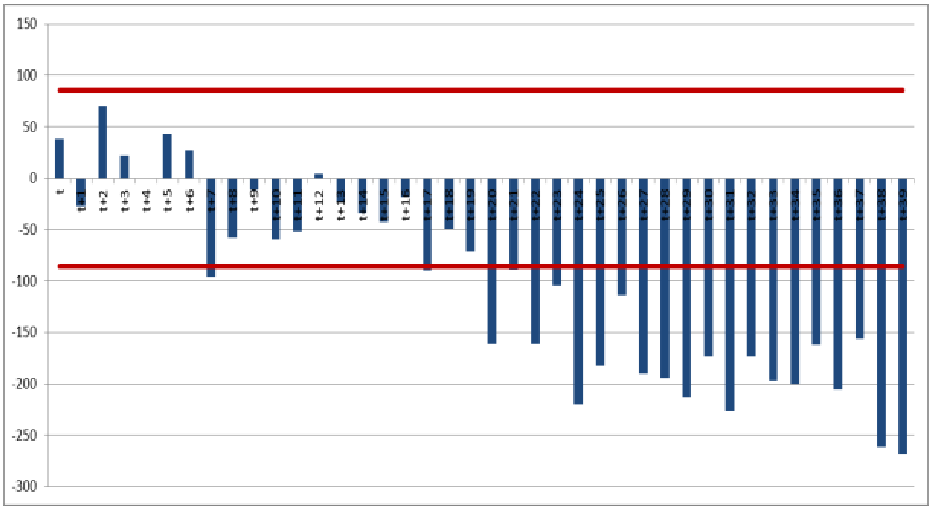
Source: processed by SAS software

The ARIMA $(1,0,0)(0,1,0)_7$ was selected because it has the smallest AIC, SBC, and RMSE values compared to the other pre-intervention model candidates, and it is stated as follows

$$\hat{Y}_t = \frac{36.5416}{(1 - 0.5058B^1)(1 - B^7)} \tag{12}$$

3.3 Intervention Model

The formation of the first and second intervention models are determined by selecting the order in which they are formed on the residual plots obtained by the difference from the intervention period and the forecast result of the pre-intervention model, as stated in **Figure 1**.



Source: processed by SAS software

Figure 1. Residual plot of the first intervention

Based on the diagram, after the trial-and-error process, the first intervention order selected is b = 7, s = (12, 13), and r = 1. The significance of the estimated parameters relating to the first intervention model is shown in **Table 2**.

Table 2. Estimation and Significance Of The Parameters Of The First Intervention Model

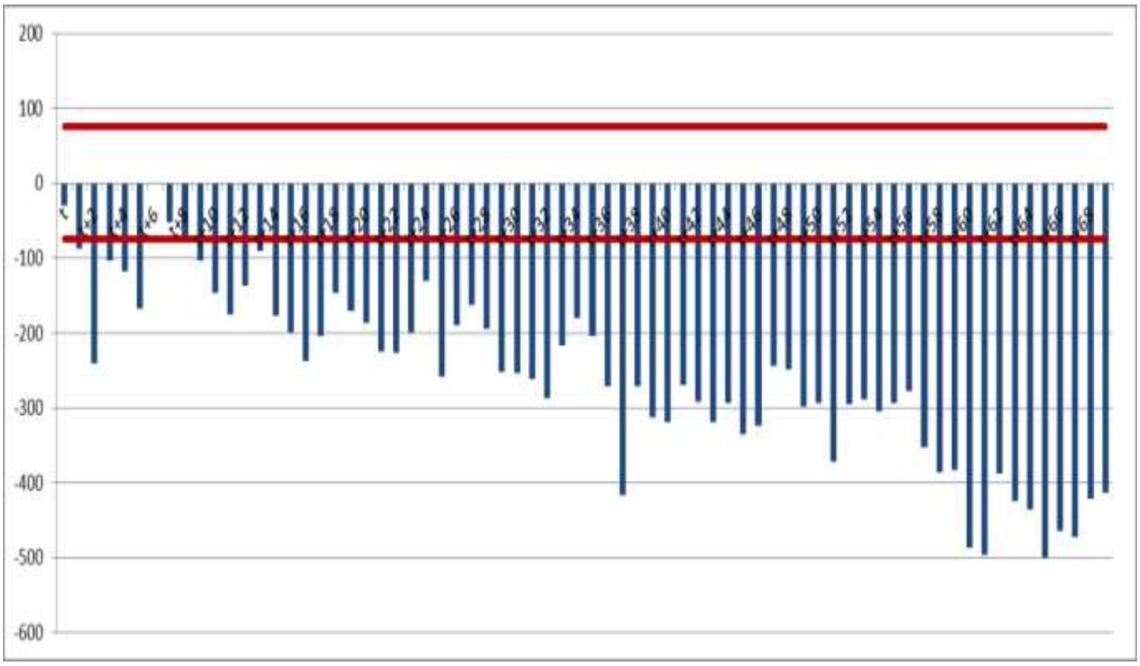
Parameters	Estimation	t-values	P-Value
M	35.4795	3.89	0.0003*
ϕ_1	0.3421	2.19	0.0337*
$\omega_{0\ 7}$	-110.2022	-4.40	<0.0001*
$\omega_{12\ 7}$	66.9825	-2.76	0.0084*
$\omega_{13\ 7}$	110.1766	4.41	<0.0001*
$\delta_{1\ 7}$	-0.5997	-4.56	<0.0001*

Source: processed by SAS software

It was further stipulated that all the first intervention model parameters are significant. The next step is the diagnostic test carried out on the first intervention, including the white noise assumption analysis and normality error. Using the Ljung-Box Statistics, it was discovered that the p-value > alpha = 5%, therefore, the model fulfills the white noise assumption. Using the Kolmogorov Smirnov test, it was discovered that the p-value is 0.15 (more than alpha = 5%), therefore, the model fulfills the normal distribution error assumption. The first intervention model is stated as follows.

$$\hat{Y}_t = \left(\frac{-110.2022 + 66.9825B^{12} + 110.1766B^{13}}{1 - 0.5997B^1}\right)B^7 S_{1t} + \frac{35.4795}{(1 - 0.3421B^1)(1 - B^7)} \tag{13}$$

The formation of the second (final) intervention model is derived from the determination of the orders on the residual plot, as shown in **Figure 2**.



Source: processed by SAS software

Figure 2. Residual plot of the second intervention

After repeated trial and error processes, it was discovered that none of the orders met the white noise and normality error assumptions. The selection of provisional models is based on the smallest AIC, SBC, and RMSE values, i.e., the orders that have the least values on the three criteria, while those selected for the second intervention are b = 2, s = (4,9,22,23), and r = 1.

Upon further investigation, both assumption tests do not fulfill the second intervention model due to outliers on the model. Kaiser and Maravall [15] examined the impact caused, namely seasonal outliers of level shift-type also called seasonal level shift (SLS) outlier on models using airline passenger data. The study reported that when an outlier effect is ignored (outlier adjustment), it causes the model not to be able to meet both the error independence and normality error. In this study, one outlier was discovered in the second intervention model, namely the SLS type, on the 137th observation or precisely in May 2020. It indicates that an outlier was detected on the second intervention model, and its effect was included until the model met the assumption test.

Afterward, seven outliers were identified in the second intervention model, as shown in Table 3.

Table 3. Outliers identified in the second intervention model

Time	Observation	Period	Type	Estimation	Chi-Square	P-Value
$(T_2 + 37)$	114	June 2018	AO	-156.4550	26.22	<0.0001*
$(T_2 + 60)$	137	May 2020	LS	-105.7020	15.34	<0.0001*
$(T_2 + 40)$	117	September 2018	AO	-70.5209	6.45	0.0111*
$(T_2 + 10)$	87	March 2016	AO	-68.8971	6.54	0.0105*
$(T_2 + 61)$	138	June 2020	AO	-70.4823	7.56	0.0060*
$(T_2 + 13)$	90	June 2016	AO	68.0130	7.65	0.0057*
$(T_2 + 51)$	128	August 2019	AO	-61.6659	6.43	0.0112*

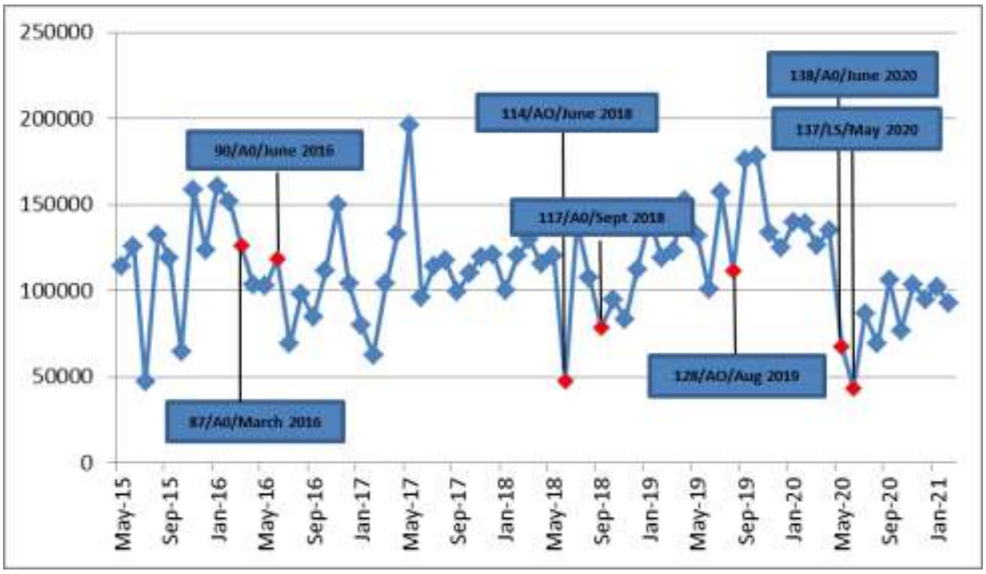
*) significant at 5% level
Source: processed by SAS software

The data relating to its period and the residual plot, i.e., the specific period in which the outliers are located, shows a fairly drastic value of HRC/P import volume compared to the others, as shown in Figure 3 and 4. Based on these diagrams, the periods where there is an outlier show the value of the import volume of HRC/P, which is quite different from the others. In the 114th observation (June 2018), a high decrease in the volume of HRC/P imports was recorded in July 2015. The first response of the second intervention was set as order b in this model. The import volume of HRC/P in June 2018 was 47,481,745 tons, which in the previous month reached 120,352,449 tons. There was a decrease of 60.55 percent in the volume of HRC/P imports in June 2018.

Referring to [16], in June 2018, an increase of 1.046 million tons or approximately 24.44 percent, was recorded in the sales volume of PT Krakatau Steel Tbk. The product with the largest increase in sales volume was HRC, with total sales of 576,652 tons or increase of 47.10 percent. This indicates a decrease in the volume of HRC/P imports due to an increase in sales of products in the country. It depicts that domestic products are consumed rather than imported ones.

Subsequently, the 137th observation made in May 2020 was identified as an outlier type, and LS also experienced a drastic decrease in the volume of HRC/P imports due to the covid-19 pandemic. Cumulatively in 2020, there was a decrease in HRC/P imports from 1,186,161 tons to 1,649,937 tons [17]. The second intervention residual plot in Figure 4 shows that the outlier on the 114th (T_2+ 37), 137th (T_2+ 60), and 138th observations (T_2+ 61) indicates a significant negative value.

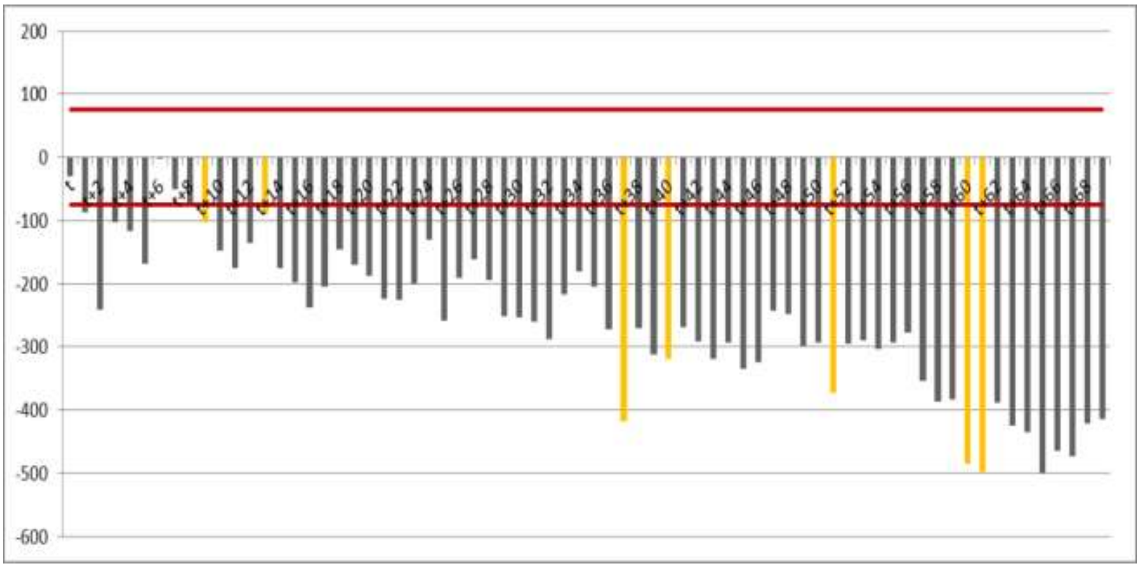
The outlier on the 128th observation (T_2+ 51) in Figure 3 does not show a drastic decrease in the volume of HRC/P imports. However, based on the residual plot (T_2+ 51) in Figure 4, the residual value is fairly negative and shows a considerable decrease in the volume of HRC/P imports.



Source: processed by SAS software

Figure 3. Data of the Second Intervention Period with Outliers Information

Figure 4 shows that the residual plots (T_2 + 10) and (T_2 + 13) values are quite extreme because it is lower than the others. The outliers were then added to the model until the entire scheme met all assumption tests.



Source: processed by SAS software

Figure 4. Residual plot of Second Intervention with Outliers Information

The significance of the estimated parameters associated with the second intervention model after an outlier was added is shown in **Table 4**. In addition, all parameters of the second intervention model are significant. The next step is to perform a diagnostic test, including the white noise assumption and normality error analyses.

Table 4. Estimation and Significance of Parameters of the Second Intervention Model After Added Outlier

Parameters	Estimation	*t*-values	P-Value
M	21.8108	3.20	0.0019*
ϕ_1	0.4256	4.26	<0.0001*
$\omega_{0\ 7}$	-103.1024	-4.23	<0.0001*
$\omega_{12\ 7}$	59.8671	2.57	0.0116*
$\omega_{13\ 7}$	104.0937	4.40	<0.0001*
$\delta_{1\ 7}$	-0.6180	-5.01	<0.0001*
$\omega_{0\ 2}$	-171.7197	-6.82	<0.0001*
$\omega_{4\ 2}$	-62.4502	-6.11	<0.0001*
$\omega_{9\ 2}$	166.1063	5.81	<0.0001*
$\omega_{22\ 2}$	-77.6822	-3.07	0.0028*
$\omega_{23\ 2}$	100.2232	3.91	0.0002*
$\delta_{1\ 2}$	-0.3736	-4.20	<0.0001*
I_{AO114}	-157.5999	-6.70	<0.0001*
I_{LS137}	-104.9939	-4.92	<0.0001*
I_{AO117}	-66.3362	2.82	0.0058*
I_{AO87}	-103.4835	-3.67	0.0004*
I_{AO138}	-69.7663	-2.91	0.0045*
I_{AO90}	81.4638	3.00	0.0034*
I_{AO128}	-70.0754	-2.97	0.0038*

Source: processed by SAS software

Based on Ljung-Box Statistics, the p-value is greater than alpha = 5%. Therefore, the model fulfills the white noise assumption. Based on the Kolmogorov Smirnov test, the D statistics value is 0.0676, and the p-value is greater than alpha = 5%. It was concluded that the model fulfills the normality errors assumption. Therefore, the second intervention model (final) selected is the one with an additional outlier which is stated as follows.

$$\begin{aligned}\hat{Y}_t =&\\ &\left(\frac{-103.1024 + 59.8671B^{12} + 104.0937B^{13}}{1 - 0.6180B^1}\right)B^7 S_{1t}\\ &- \left(\frac{171.7197 + 162.4502B^4 - 166.1063B^8 + 77.6822B^{22} - 100.2232B^{23}}{1 - 0.3736B^1}\right)B^2 S_{2t}\\ &- \frac{21.8108}{(1 - 0.4256B^1)(1 - B^7)} - 157.5999I_t^{114} - \frac{104.9939}{1 - B}I_t^{137} - 66.3362I_t^{117} - 103.4835I_t^{87}\\ &- 69.7663I_t^{138} + 81.4638I_t^{90} - 70.0754I_t^{128} \qquad (14)\end{aligned}$$

The magnitude of the impact of the intervention is calculated after obtaining the model for each of them.

3.4 The impact of the intervention

The impact of the intervention is obtained from the difference between the forecasting value of the final and the pre-intervention models [9]. However, before calculating the impact of interventions, the return of data is carried out into its initial form because the data used previously is the resulting data of transformation, also called inverting data. The first intervention data is obtained from the difference between the forecasting results of the first and pre-intervention models. Meanwhile, the impact of the second (final) intervention is obtained from the difference between the forecasting results of the second and the first intervention models. The impact of the first intervention is shown in **Table 5**.

Table 5. Impact of the First Intervention

Time	Period	First Intervention	Pre-Intervention	Magnitude effect	Percentage
T_1+7	Aug-12	143,026.01	195,112.23	-52,086.22	-26.70
T_1+8	Sept-12	169,737.57	242,074.04	-72,336.46	-29.88
T_1+9	Oct-12	182,604.78	191,003.26	-8,398.49	-4.40
….	….	….	….	….	….
$T_1 + 36$	Jan-15	189,449.87	407,269.37	-217,819.50	-53.48
$T_1 + 37$	Feb-15	169,615.48	340,128.89	-170,513.41	-50.13
$T_1 + 38$	Mar-15	181,382.72	418,896.06	-237,513.34	-56.70
$T_1 + 39$	Apr-15	198,438.18	398,565.83	-200,127.65	-50.21

The impact of the first intervention was felt in August 2012, which caused a decrease of 26.70 percent in the volume of imports of HRC/P. In the subsequent month, the impact of the first intervention was greater, which caused a decrease of 29.88 percent in the volume of imports. The impact of the first intervention was felt throughout the entire period. However, it tends to fluctuate, irrespective of the fact that it was felt for a more extended period, and tends to get bigger therefore, it was presumed to be permanent **[1]**.

The impact of the second intervention is shown in **Table 6**. Initially, it lowered the volume of HRC/P imports in July 2015 by 71.74 percent, more significant than the first intervention period. In the subsequent month, the second intervention reduced the imports volume of HRC/P and the impact by 51.73 percent. Overall, this reduced the volume of HRC/P imports till the end of the intervention period. The magnitude of the impact fluctuated, although, it was getting bigger. Based on this condition, the impact of the second intervention is permanent **[1]**, **[18]**.

Table 6. Impact of the second intervention

Time	Period	Second Intervention	First Intervention	Magnitude effect	Percentage
T_2+2	Jul-15	59,211.34	209,541.56	150,330.22	-71.74
T_2+3	Aug-15	105,146.30	217,834.84	112,688.54	-51.73
T_2+4	Sept-15	103,827.47	213,620.80	109,793.33	-51.40
T_2+5	Oct-15	86,666.77	177,574.25	-90,907.48	-51.19
…..	…..	…..	…..	…..	…..
T_2+66	Nov-20	84,052.97	617,862.18	533,809.21	-86.40
T_2+67	Dec-20	85,259.80	610,752.10	525,492.30	-86.04
T_2+68	Jan-21	96,780.72	548,652.19	451,871.47	-82.36
T_2+69	Feb-21	103,533.62	515,613.75	412,080.14	-79.92

4. CONCLUSIONS

The interventions used are the 5 percent and 15 percent of the MFN tariff-setting policies to reduce the volume of HRC/P imports that increased since 2009. The ARIMA $(1,0,0)(0,1,0)_7$ was selected as pre-intervention model. Both interventions had a considerable impact and were described as permanent. During the implementation of the second intervention period, a policy of increasing MFN rates by 15 percent, some outliers were found, namely AO and LS types. This indicated that the model used was unable to meet the white noise assumption test. In addressing this, the outliers are added to the model, and after further investigation, it was discovered that they coincided with several important interventions that had a fairly drastic change in data patterns. The impact of the first intervention in the form of setting the HRC/P import duty rate at 5 percent was first felt 7 months after the policy came into force, namely in August 2012. The impact of the second intervention in the form of an increase in the HRC/P import duty rate by 15 percent was first felt 2 months after the policy came into force, namely in July 2015. A limitation of this research is that this model cannot include other independent variables in the modeling.

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