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FORECASTING NUMBER OF INTERNATIONAL TOURIST ARRIVALS USING MULTI INPUT INTERVENTION ARIMA MODEL

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ABSTRACT

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In 2020, the Covid-19 pandemic caused a very significant impact resulting in the drastic decline in the number of international tourist visits. As the Covid-19 pandemic ends, the government reopen international flight to Indonesia in early 2022 to remark the revival of the tourism industry. To determine how big the impact of the Covid-19 pandemic as well as the recovery process on international tourist visits through Soekarno-Hatta, Ngurah-Rai, and Kualanamu airports in the coming period, forecasting is needed. The forecasting method utilized in this study is multi-input intervention analysis. The first input is caused by the outbreak of Covid-19 pandemic, while the second input is due to the international flight reopening. The type of intervention variable chosen is a step function because both inputs give permanent effect to the international tourist arrivals. The data used in this study are monthly international tourist arrivals based on the entrances to Soekarno-Hatta, Ngurah-Rai, and Kualanamu International Airports from January 2008 to September 2023, taken from the Central Bureau of Statistics website. Based on the results, it was found that the number of international tourist arrivals entering Soekarno-Hatta airport can be modelled using SARIMA $(0,1,1)(0,1,0)^{12}$ with (b=2, s=1, r=0) and (b=2, s=[3], r=0) for first and second input of intervention variable, respectively. Furthermore, the number of international tourist visits through Ngurah-Rai airport was more appropriate to be modelled using SARIMA $(1,1,1)(0,1,1)^{12}$ with intervention inputs (b=1, s=[2], r=0) and (b=4, s=0, r=1). In Kualanamu airport, the first intervention order is equal to that in Ngurah-Rai airport, with (b=3, s=[3], r=0) for second intervention input and SARIMA $(0,1,1)(1,1,1)^{12}$ for pre-intervention data. The forecast results show that the number of international tourist arrivals entering Soekarno-Hatta, Ngurah-Rai, and Kualanamu international airports are already recovered to pre-pandemic conditions at a quick pace

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1. INTRODUCTION

The sector of tourism industry plays an important role in improving the country's economy, especially in reducing the number of unemployment and increasing the productivity of a country. One of the countries whose economy is supported by the tourism sector is Indonesia. Indonesia has very diverse ethnicities and cultures that attract tourists, both domestic and foreign. Through the tourism industry sector, each region can develop their potential which will have an impact on their economic growth. However, at the beginning of 2020, the world was shocked by the outbreak of Coronavirus Disease (Covid-19) [1]. The Covid-19 pandemic has had a very significant impact on Indonesian tourism. The decline in the number of both domestic and foreign tourists because of the implementation of large-scale social restrictions in several regions, as well as the closure of international access from various countries have made the tourism industry slump [2]. Throughout 2020, the number of foreign tourist visits was recorded at only 4.05 million visits. Meanwhile in 2021, the number of foreign tourist visits was only recorded at 1.56 million visits, a decrease of 61.57% compared to that in 2020. During 2022, the number of foreign tourist visits to Indonesia reach 5.47 million, an increase of 251.28 percent compared to that in [3]. Therefore, the outbreak of Covid-19 pandemic in 2020 and the recovery from that pandemic in 2022 become the intervention variables affecting the number of international tourist arrivals to Indonesia.

One time series method that is often used to describe how external and internal interventions influence the time series data pattern is intervention analysis [4]. Intervention analysis can be viewed as a type of time series regression analysis in which one or more predictor variables at evenly spaced points in time are postulated to have an impact on the response variable observed at the same point in time [5]. Predictor variables can be events such as government policies, natural disasters, promotions, etc. with previously known occurrence times [6]. Intervention models on time series data were first used by Box and Tiao [7] in their research on the effects of enforcing machine design rules, which were thought to have an influence on oxidant pollution levels in Los Angeles. Some researchers have applied intervention analysis to measure the impact of financial crisis [8], the impact of health intervention [9], the effect of economic activity [10], the impact of government policies [11], and the impact of Covid-19 pandemic [12].

In Indonesia, forecasting international tourist arrivals has been conducted using some methods, such as Seasonal Autoregressive Integrated Moving Average with Exogenous Variables (SARIMAX) [13], multi-input intervention ARIMA [14], and machine learning algorithms [15]. There are some researchers focus on predicting the number of international tourist arrivals by considering the impact of Covid-19 pandemic from outside Indonesia including [16], [17], [18], [19], [20], [21]. To find out how big the impact of the Covid-19 pandemic as well as the recovery process from that pandemic, this research is aimed to forecast the number of international tourist arrivals to Indonesia entering three international airports which are Soekarno-Hatta, Ngurah-Rai, and Kualanamu. The forecasting method that will be used in this study is intervention ARIMA model with two intervention inputs including the outbreak of Covid-19 pandemic in 2020 and the reopening of international flight in 2022.

2. RESEARCH METHODS

The intervention analysis is a technique to evaluate the impact of external events (such as holidays, strikes, sales promotion, disaster, and other policy changes) on the time series data. The general form of intervention model with single intervention variable I_t at time series data Z_t following Equation (1):

$$Z_t = f(I_t) + N_t$$
$$Z_t = \frac{\omega_s(B)}{\delta_r(B)} B^b I_t + \frac{\theta_q(B)\Theta_Q(B^S)}{\phi_p(B)\Phi_P(B^S)} a_t \tag{1}$$

where

Z_t : response variable at time-t
I_t : intervention input at time-t
b : the delay time or the first time the intervention has an effect
r : the pattern of the impacts of an intervention
s : the time required for the intervention's impact on being stable

N_t : pre-intervention model, according to ARIMA model
$\omega_s(B)$: $\omega_0 - \omega_1 B - \omega_2 B^2 - \cdots - \omega_s B^s$
$\delta_r(B)$: $1 - \delta_1 B - \delta_2 B^2 - \cdots - \delta_r B^r$
$\theta_q(B)$: $1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$
$\Theta_Q(B^S)$: $1 - \Theta_1 B^S - \Theta_2 B^{2S} - \cdots - \Theta_Q B^{QS}$
$\phi_p(B)$: $1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$
$\Phi_P(B^S)$: $1 - \Phi_1 B^S - \Phi_2 B^{2S} - \cdots - \Phi_P B^{PS}$

The intervention ARIMA model for multiple intervention inputs can be written as follows:

$$Z_t = \sum_{j=1}^{k} \frac{\omega_{sj}(B)}{\delta_{rj}(B)} B^{bj} I_{jt} + N_t \tag{2}$$

where $I_{jt}, j = 1,2,\dots,k$ are intervention inputs variables. These intervention variables can be either step or pulse functions. Step function can be utilized if the intervention occurs in a long period of time or has permanent effect. The step function in the intervention model can be written in **Equation (3)**. If the intervention occurs within a certain period or results in temporary effect, then we can utilize pulse function as written in **Equation (4)**.

$$S_t^{(T)} = \begin{cases} 0, & t < T \\ 1, & t \geq T \end{cases} \tag{3}$$

$$P_t^{(T)} = \begin{cases} 1, & t < T \\ 0, & t \geq T \end{cases} \tag{4}$$

To see whether a time series intervention data is included in the step function or pulse function, it can be seen from the graph or plot of the residual **[21]** which is the response to the intervention (see **Figure 1** for $b = 1$ and $0 < \delta < 1$ **[21]**). Note that if $0 \leq \delta \leq 1$. If $\delta = 1$, then the impact increases linearly without bond. Otherwise, the response is gradual if $0 < \delta < 1$.

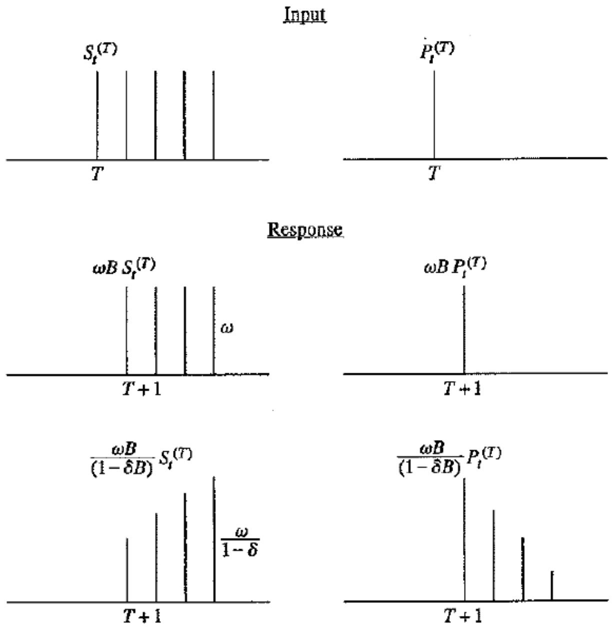


Figure 1. The Intervention Responses for Step and Pulse Function

The order of b, s, and r are important in intervention modeling. This order can be determined by looking at the ARIMA residual plot from the data before the intervention. The limit used is $\pm 3\sigma$. Order b indicates the order in which the impact of the intervention begins to take effect. The residual graph can go up or down at the time of the intervention or after the intervention. Order s is determined since the response weight movement begins to decrease or starts to be within significant limits. Order r is the next r time lag (after b and s) when the data has formed a clear pattern. With several possible combinations of orders b, s, and r, a trial-and-error process is carried out then the combination of $b - s - r$ order that produces the best model for forecasting is chosen **[21]**.

Perform diagnostic checking by seeing whether the residual is white noise and normally distributed. Only intervention models that have met diagnostic checking can be used for forecasting. Finally, after finding the best model by looking at the Akaike Information Criterion (AIC) and Mean Absolute Percentage Error

(MAPE) values so that it is concluded that the model can be used, then forecasting with the intervention model can be done [21].

The data used in this study is secondary data taken from the Central Bureau of Statistics about the monthly number of international tourist arrivals based on the entrance of Soekarno-Hatta, Ngurah-Rai, and Kualanamu International Airports. The data from January 2008 until December 2022 are utilized as in-sample, whereas the out-sample data are taken from January to September 2023.

The procedures to perform the intervention ARIMA model with two inputs can be written as follows:

Step 1 Perform the ARIMA Box-Jenkins procedures for the pre-intervention data (January 2008-December 2019). Then, forecasting the data at first intervention period using the pre-intervention ARIMA model. Furthermore, compute the response function at first intervention period, which is the difference between actual and forecasting data at first intervention period.

Step 2 Identify the order of b, s, and r for first intervention based on the plot of first response function, then estimate the parameter of first intervention ARIMA model. In addition, forecasting the data at the second intervention period using the first intervention model. The forecasting value at the second intervention period is utilized to obtain the response function at second intervention period.

Step 3 Identify the order of b, s, and r for second intervention based on the plot of second response function, then estimate the parameter of second intervention ARIMA model. Moreover, evaluate the magnitude and duration impact of the first and second interventions on time series.

Step 4 Check the residual assumptions including white noise and normal distribution. If residuals satisfy those assumptions, the intervention ARIMA model can be utilized to forecast until k steps ahead.

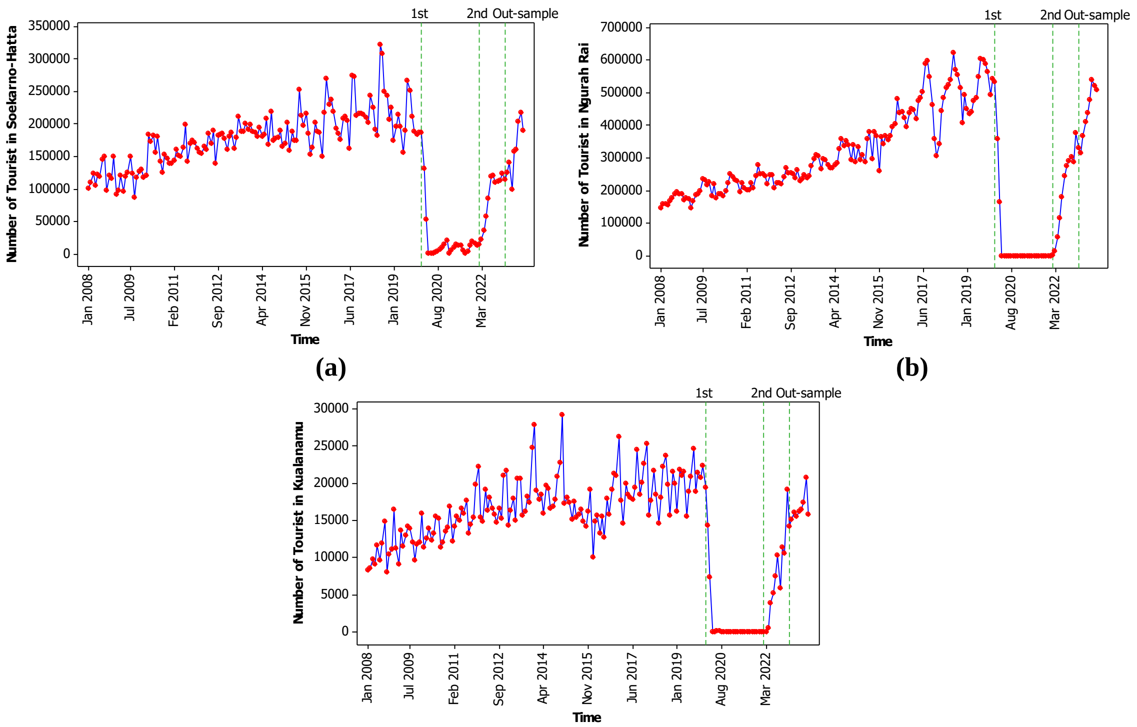
3. RESULTS AND DISCUSSION

This section provides the descriptive statistics and multi-input intervention ARIMA analysis for international tourist arrivals in Soekarno-Hatta, Ngurah-Rai, and Kualanamu airports. Based on Figure 2, the number of international tourist arrivals in each airport has three vertical reference line indicating first input of intervention, second input of intervention, and the start of out-sample data (each variable has nine out-sample data). The first input is caused by an outbreak of Covid-19 pandemic in January 2020 ($t = 145$) such that the data experienced a drastic decline with permanent effect until January 2022. Two years later, starting in February 2022 ($t = 170$), Indonesia government reopen the international flight to Indonesia resulting in the significant increasing value of the international tourist arrivals. Therefore, the number of international tourist arrivals in each airport is analyzed using intervention ARIMA model with first and second inputs are determined as in Equation (5) and Equation (6), respectively.

$$S_{1t}^{(145)} = \begin{cases} 1, & 145 \leq t < 170 \\ 0, & t < 145 \text{ and } t \geq 170 \end{cases} \tag{5}$$

$$S_{2t}^{(170)} = \begin{cases} 1, t \geq 170 \\ 0, t < 170 \end{cases} \tag{6}$$

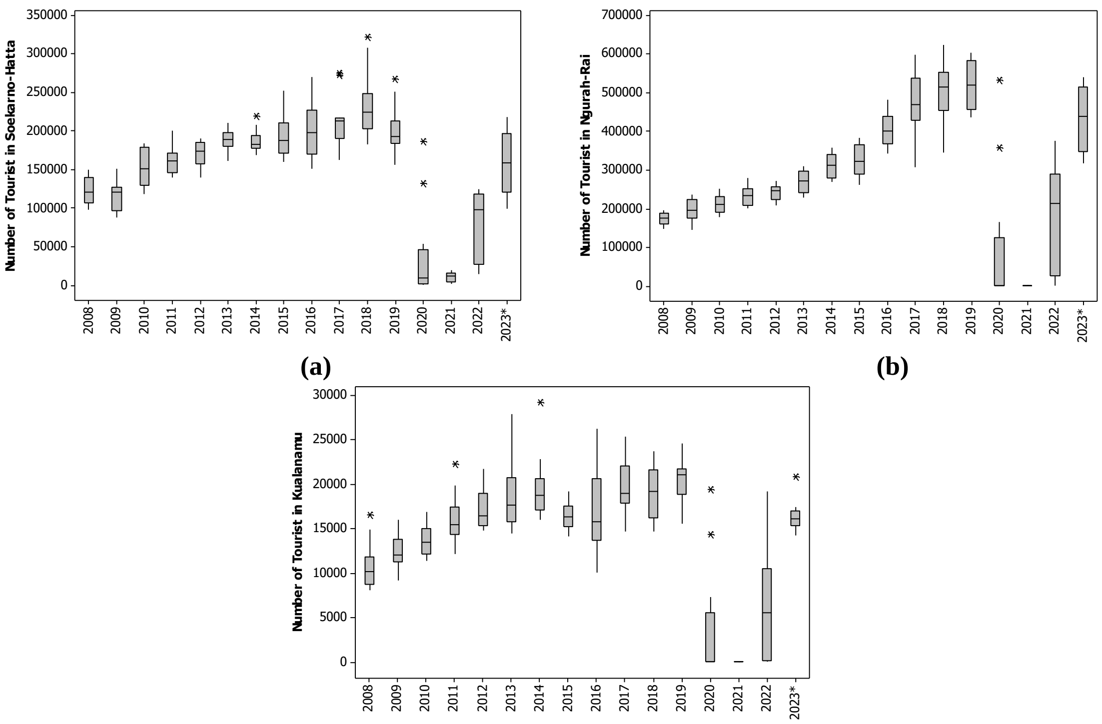
The next analysis, we gather the international tourist arrivals data in every year, then build the boxplot (It is important to highlight that the boxplot in 2023 only utilize the out-sample data from January until September 2023). As depicted in Figure 3, the boxplot in 2020 has two outliers indicating the international tourist arrivals in January and February 2020. The Covid-19 pandemic was firstly outbreak in China in December 2019, but the first time it was reported to enter Indonesia on early March 2020. Hence, the number of international tourist arrivals entering Soekarno-Hatta, Ngurah-Rai, and Kualanamu airports were declining up to 70 percent in March 2020. The boxplots in 2021 near to zero denoting very small amount of international tourist arrived in those three airports. Moreover, the boxplots in 2022 have the largest range compared to the ones in another year indicating the transition period where the international flights to Indonesia are reopened and the Covid-19 pandemic is disappeared continuously.



(a) (b)

(c)

Figure 2. Time Series Plot of International Tourist Arrival's Number in (a) Soekarno-Hatta, (b) Ngurah-Rai, and (c) Kualanamu Airports



(a) (b)

(c)

Figure 3. Boxplot of International Tourist Arrival's Number in (a) Soekarno-Hatta, (b) Ngurah-Rai, and (c) Kualanamu Airports

The first step to build intervention model is perform the ARIMA Box-Jenkins procedure for pre-intervention data. For international tourist arrivals entering Soekarno-Hatta airport, the data already stationary after taking differencing at non-seasonal lag 1 and seasonal lag 12. According to the ACF and PACF of stationary data, we can have two tentative models which are SARIMA $(0,1,1)(1,1,1)^{12}$ and SARIMA $(0,1,1)(0,1,0)^{12}$. The best model to predict number of international tourist arrivals in Soekarno-Hatta for pre intervention is SARIMA $(0,1,1)(0,1,0)^{12}$ because its parameter already significant, and its residuals already satisfy white noise and normal assumptions. Furthermore, the plot of residuals obtained from the difference between actual and fitted value from ARIMA pre-intervention model can be seen in **Figure 4(a)**.

Table 1. Multi-input Intervention ARIMA Model Selection for Number of International Tourist Arrival

Variable	Model	Order for Second Intervention	Out-sample MAPE	In-sample AIC
Soekarno-Hatta	1	$b=3, s=1, r=0$	0.3360 %	3754.27
	2	$b=2, s=[2], r=0$	0.3382 %	3739.508
	3	$b=2, s=[3], r=0$	**0.2357 %**	**3715.415**
Ngurah-Rai	1	$b=4, s=0, r=1$	0.0679 %	**4084.511**
	2	$b=3, s=0, r=1$	**0.0671** %	4104.925
Kualanamu	1	$b=3, s=[3], r=0$	0.1055 %	**3093.602**
	2	$b=5, s=0, r=1$	**0.1005** %	3098.370

From the plot of residual (or usually known as response function) in the first intervention displayed in **Figure 4(a)**, we know that the Covid-19 pandemic caused the response function goes out from the $\pm 3\sigma$ limits. Based on these limits, the first lag comes out at lag $T+2$ (2 months after the first intervention happened) and the plots exhibit an exponential pattern. Thus, the order of first intervention for Soekarno-Hatta airport is $(b=2, s=1, r=0)$. Since all parameters of first intervention ARIMA model already significant, the analysis is continued by performing the second intervention with similar procedures as previous intervention. From the second response function (see **Figure 4(b)**), we can obtain three tentative orders of second intervention model which are $(b=3, s=1, r=0), (b=2, s=[2], r=0)$, and $(b=2, s=[3], r=0)$. **Table 1** shows the out-sample MAPE and in-sample AIC value for those tentative models. As a result, the best intervention ARIMA model for forecasting international tourist arrivals entering Soekarno-Hatta airport has $b=2, s=[3]$, and $r=0$ for second intervention order. **Table 2** exhibits the parameter estimation of final intervention ARIMA model for international tourist arrivals in Soekarno-Hatta airport. Mathematically, that model can be written as follows:

$$Z_t = (-122612 - 41038.1B)(B^2)S_{1,t}^{(145)} + (-113719 + 50082.7B^3)(B^2)S_{2,t}^{(270)} + \frac{(1-0.60985\mathrm{B})a_t}{(1-B)(1-B^{12})} \quad (7)$$

$$Z_t = -122612S_{1,t-2}^{(145)} - 41038.1S_{1,t-3}^{(145)} - 113719S_{2,t-2}^{(170)} + 50082.7S_{2,t-5}^{(170)} + \frac{a_t - 0.60985a_{t-1}}{(1-B)(1-B^{12})}$$

Table 2. Parameter Estimation of Multi-input Intervention ARIMA Model in Soekarno-Hatta Airport

Model	Parameter	Estimated Value	S.E.	t	p-value
SARIMA $(0,1,1)(0,1,0)^{12}$	$\hat{\theta}_1$	0.60985	0.06496	9.39	<.0001
1st Intervention	$\hat{\omega}_{01}$	-122612	15425.5	-7.95	<.0001
$b=2, s=1, r=0$	$\hat{\omega}_{11}$	41038.1	13351.5	3.07	0.0025
2nd Intervention	$\hat{\omega}_{02}$	-113719	22648.8	-5.02	<.0001
$b=2, s=[3], r=0$	$\hat{\omega}_{32}$	-50082.7	18859	-2.66	0.0087

Table 3. Parameter Estimation of Multi-input Intervention ARIMA Model in Ngurah-Rai Airport

Model	Parameter	Estimated Value	S.E.	t	P-value
SARIMA $(1,1,1)(0,1,1)^{12}$	$\hat{\theta}_1$	-0.93386	0.13421	-6.96	<.0001
	$\hat{\Theta}_1$	0.8346	0.0487	17.14	<.0001
	$\hat{\phi}_1$	-0.89378	0.16424	-5.44	<.0001
1st Intervention	$\hat{\omega}_{01}$	-97425.7	25908.2	-3.76	0.0002
$b=1, s=[2], r=0$	$\hat{\omega}_{21}$	114793.1	25854.5	4.44	<.0001
2nd Intervention	$\hat{\omega}_{02}$	41905.9	21225.5	1.97	0.0500
$b=4, s=0, r=1$	$\hat{\delta}_{12}$	0.92404	0.07746	11.93	<.0001

The best multi-input intervention ARIMA model to predict the number of international tourist arrivals entering Soekarno-Hatta airport in **Equation (7)** has residuals that satisfy white noise and normal assumptions. This model is then utilized to forecast international tourist arrivals in Soekarno-Hatta for October 2023 until September 2024 as displayed in **Table 5**. The time series plot comparison between actual and fitted value of international tourist arrivals entering Soekarno-Hatta airport can be seen in **Figure 5(a)**. After decreasing significantly for more than two years, the number of international tourist arrivals from 2022 until nowadays have shown a rapid recovery like conditions before the pandemic. In early 2023, the actual and fitted values have shown a significant increase, where the forecasting value for 2024 is almost equal to the condition in last 2019 indicating the better revival of tourism sector.

Table 4. Parameter Estimation of Multi-input Intervention ARIMA Model in Kualanamu Airport

Model	Parameter	Estimated Value	S.E.	t	P-value
SARIMA $(0,1,1)(1,1,1)^{12}$	$\hat{\theta}_1$	0.56047	0.07284	7.69	<.0001
	$\hat{\Theta}_1$	0.91504	0.05377	17.02	<.0001
	$\hat{\Phi}_1$	0.46252	0.10699	4.32	<.0001
1st Intervention	$\hat{\omega}_{01}$	-5014.8	1355.2	-3.7	0.0003
$b = 1, s = [2], r = 0$	$\hat{\omega}_{21}$	11323.7	2008.4	5.64	<.0001
2nd Intervention	$\hat{\omega}_{02}$	-8742.3	2858.3	-3.06	0.0026
$b = 3, s = [3], r = 0$	$\hat{\omega}_{32}$	-3905.2	2106.3	-1.85	0.0656

The number of international tourist arrivals entering Ngurah-Rai airport is analyzed using similar steps as utilized in previous data. The best model for pre-intervention data in Ngurah-Rai airport is SARIMA $(1,1,1)(0,1,1)^{12}$. According to the response function for first input in Ngurah-Rai (see **Figure 4(c)**), we can obtain all significant parameters for first input with order $b = 1, s = [2]$, and $r = 0$. This model is applied to forecast for first intervention, then the plot of residuals (or response function) for second intervention in Ngurah-Rai airport is obtained as in **Figure 4(d)**. We have two tentative orders of $b, s,$ and r with all significant parameters for the second intervention in Ngurah-Rai airport, which are $(b = 4, s = 0, r = 1)$ and $(b = 3, s = 0, r = 1)$ (see **Table 1**). Although the first model has slightly larger out-sample MAPE than the second model, we choose first model as best method for forecasting number of international tourist arrivals in Ngurah-Rai airport because it has smaller in-sample AIC compared to the second model. The first model with $b = 4, s = 0,$ and $r = 1$ for second intervention order in Ngurah-Rai also support the response function in **Figure 4(d)** that the first plot goes out from 3σ limit at lag $T + 4$. Hence, the parameters of final model to forecast the number of international tourist arrivals entering Ngurah-Rai airport are displayed in **Table 3**. All parameters are already significant.

$$Z_t = (-97425.7 - 114793.1B^2)(B)S_{1,t}^{(145)} + \frac{41905.9(B^4)S_{2,t}^{(270)}}{(1 - 0.92404B)} + \frac{(1 + 0.93386B)(1 - 0.8346B^{12})a_t}{(1 - B)(1 - B^{12})(1 - 0.89378B)} \quad (8)$$

$$Z_t = -97425.7S_{1,t-1}^{(145)} - 114793.1S_{1,t-3}^{(145)} + \frac{41905.9S_{2,t-4}^{(270)}}{(1 - 0.92404B)} + \frac{(1 + 0.93386B)(1 - 0.8346B^{12})a_t}{(1 - B)(1 - B^{12})(1 - 0.89378B)}$$

The best model for forecasting international tourist arrivals in Ngurah-Rai can be written in **Equation (8)**. This model satisfies white noise and normal assumptions for its residuals. This model is applied to predict the international tourist arrivals entering Ngurah-Rai airport for the next one year starting from October 2023. The prediction value for international tourist arrivals entering Ngurah-Rai airport can be shown in **Table 5**. For the next one-year prediction, the largest value is obtained in July 2024 where more than 585 thousand of international tourist will visit Indonesia through Ngurah-Rai international airport. The time series plot comparison between actual and fitted value of international tourist arrivals entering Ngurah-Rai airport is exhibited in **Figure 5(b).**

The last analysis is conducted to obtain multi-input intervention ARIMA model for the number of international tourist arrivals entering Kualanamu airport. We obtained SARIMA $(0,1,1)(1,1,1)^{12}$ as the best model for pre-intervention data in Kualanamu airport. The response function for first input in Kualanamu airport is shown in **Figure 4(e)**. Since the first input with order $b = 1, s = [2]$, and $r = 0$ results in all significant parameters, we can forecast for first intervention and obtain the residuals for second intervention in Kualanamu airport (see **Figure 4(f)**). The in-sample AIC and out-sample MAPE from two tentative models for second order intervention in Kualanamu is presented in **Table 1**. The first model with $b = 3, s = [3]$, and $r = 0$ is selected as the best method because it has smaller in-sample AIC than the second model. **Table 4** presents the significant parameters of the final model to predict the number of international tourist arrivals entering Kualanamu airport. Mathematically, the model for international tourist arrivals in Kualanamu airport can be written in **Equation (9)**. The residuals of that model already satisfy white noise and normal assumptions, then we can obtain the forecasting value of international tourist arrivals in Kualanamu airport as shown in **Table 5**. For the next one-year prediction starting from October 2023, we obtain that in the peak of year-end holiday season in December 2023, more than 25 thousand international tourists will arrive in Kualanamu airport.

$$Z_t = (-5014.8 - 11323.7B^2)(B)S_{1,t}^{(145)} + (-8742.3 + 3905.2B^3)(B^3)S_{2,t}^{(170)} + \frac{(1-0.56047B)(1-0.91504B^{12})a_t}{(1-B)(1-B^{12})(1-0.46252B^{12})} \quad (9)$$

$$Z_t = -5014.8S_{1,t-1}^{(145)} - 11323.7S_{1,t-3}^{(145)} - 8742.3S_{2,t-3}^{(170)} + 3905.2S_{2,t-6}^{(170)} + \frac{(1-0.56047B)(1-0.91504B^{12})a_t}{(1-B)(1-B^{12})(1-0.46252B^{12})}$$

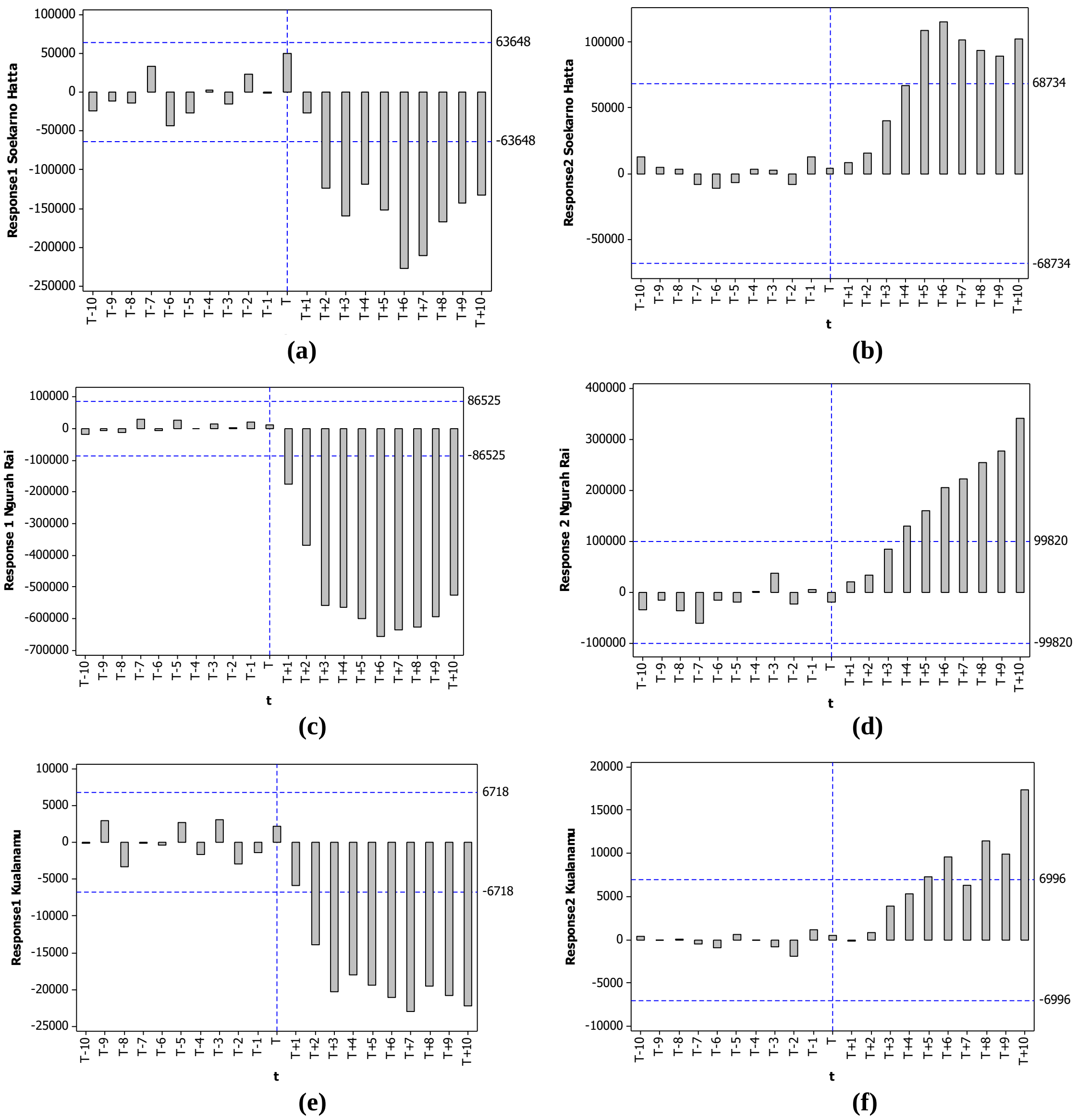


Figure 4. Plot of Response Function for (a) 1st Input Soekarno-Hatta, (b) 2nd Input Soekarno-Hatta, (c) 1st Input Ngurah-Rai, (d) 2nd Input Ngurah-Rai, (e) 1st Input Kualanamu, and (f) 2nd Input Kualanamu

Figure 5(c) presents the time series plot comparison between actual and predicted value of international tourist arrivals entering Kualanamu airport. For the preintervention, the fitted value is not significantly different from the actual value. However, during Covid-19 pandemic (between April 2020 and February 2022), the model results in high error because the fitted values following preintervention pattern (until results in negative values), but the actual values are near to zero. For the period after second intervention input, the model can capture the actual values accurately by following the linear increasing trend. Based on overall analysis, it is generally seen that the Covid-19 pandemic had a huge impact on tourism activities for more than two years. The employment opportunities and income for some aspects such as hotel occupancy and tourist attraction are directly related to tourist spending and investment in tourism. This of course will be very influential when viewed from the indirect impact of tourism on the economy of Indonesia such as hotels, restaurants, and trade, which greatly help the Indonesian economy.

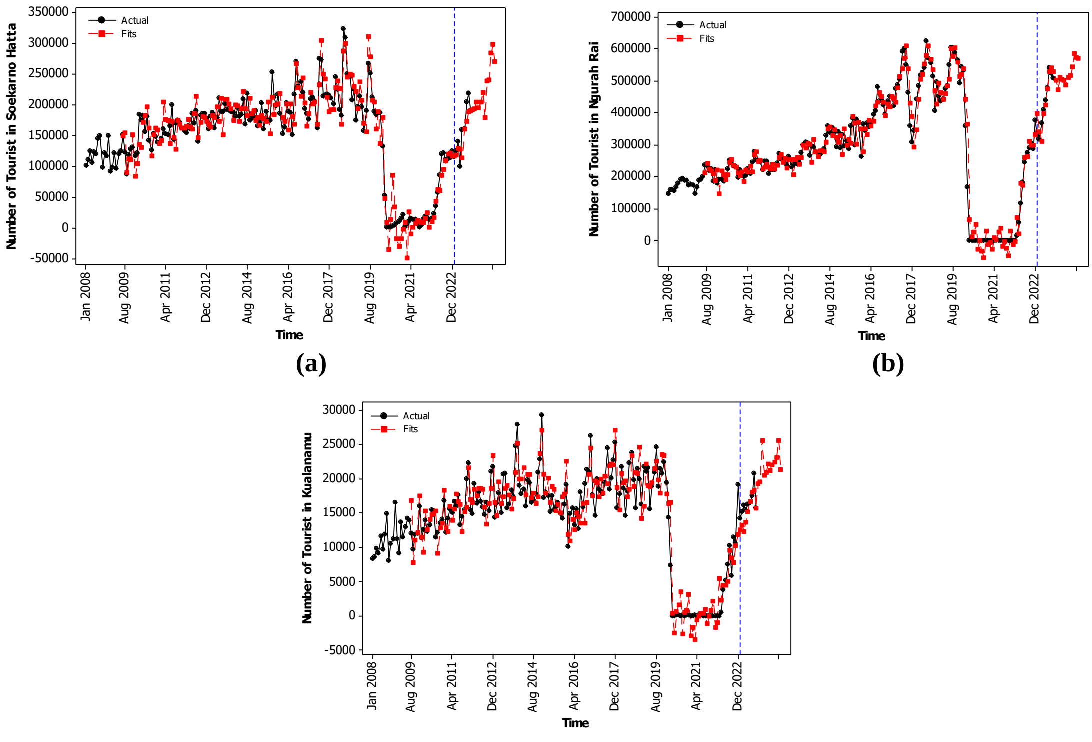


Figure 5. Time Series Plot of International Tourist Arrival's Number in (a) Soekarno-Hatta, (b) Ngurah-Rai, and (c) Kualanamu Airports

Table 5. Forecasting Result for Number of International Tourist Arrival

Month	Soekarno-Hatta	Ngurah-Rai	Kualanamu
October 2023	192020	500886	19284
November 2023	193222	472060	19531
December 2023	203968	511756	25637
January 2024	195083	503630	20473
February 2024	204702	503040	20971
March 2024	220352	488567	22150
April 2024	178782	511318	21256
May 2024	238043	515592	21978
June 2024	240607	543354	22410
July 2024	283493	585266	23176
August 2024	298005	574243	25521
September 2024	269551	570860	21352

4. CONCLUSIONS

This study obtains the multi-input intervention ARIMA model for forecasting the number of international tourist arrivals entering Soekarno-Hatta, Ngurah-Rai, and Kualanamu international airports. The analysis is performed for each airport using two inputs which are the outbreak of Covid-19 pandemic in early 2020 and the reopening of international flight to Indonesia in early 2022. Since the first input gives permanent effect for about two years and the second input brings permanent effect until the present, we utilize the step function as the inputs. The best model and intervention inputs for forecasting the international tourist arrivals entering Soekarno-Hatta, Ngurah-Rai, and Kualanamu airports are $\text{SARIMA}(0,1,1)(0,1,0)^{12}$, with $(b = 2, s = 1, r = 0) - (b = 2, s = [3], r = 0)$; $\text{SARIMA}(1,1,1)(0,1,1)^{12}$, with $(b = 1, s = [2], r = 0) - (b = 4, s = 0, r = 1)$; and $\text{SARIMA}(0,1,1)(1,1,1)^{12}$, with $(b = 1, s = [2], r = 0) - (b = 3, s = [3], r = 0)$, respectively. Those models result in out-sample MAPE equal to 0.2357%, 0.0679%, and 0.1055%, respectively. All models already satisfy white noise and normal assumptions of the residuals. The forecasting results (see Table 5) show that the number of international tourist arrivals entering three airports are trying to recover to pre-pandemic conditions at a quick pace. This means that the tourism sector can rebuild the survival of Indonesian economy after Covid-19 pandemic. In future research, the intervention model based on Poisson autoregressive can be applied to forecast number of international tourist arrivals more accurately.

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