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Modeling Airplane Passenger Volatility during the COVID-19 Crisis: A SARIMA and Intervention Analysis

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Abstract

The COVID-19 pandemic in early 2020 had a severe impact on air traffic at Indonesia's Soekarno-Hatta International Airport. This caused a sharp decline in passenger numbers in March 2020 by 21.23% compared to March 2019, resulting in significant data fluctuations that required statistical intervention. Therefore, to forecast passenger numbers during these fluctuating trends, this study used the SARIMA and Step Function Intervention models. The results showed that based on the training data, which span from January 2006 to January 2025, and testing data, which span from February 2025 to January 2026, the best SARIMA model based on the smallest AIC criterion is SARIMA$(1,1,1)(1,0,0)_{12}$, while the best Intervention model is SARIMA$(0,1,1)(1,0,0)_{12}$ with $b = 0$, $s = 26$, and $r = 0$. Based on the test data, the SARIMA model has an RMSE value of 115,290.6 and a MAPE of 7.55%, with forecast results for February 2026 to January 2027 ranging from 1,249,662 to 1,469,362 passengers per month. The Step Function Intervention model has an RMSE value of 168,199.4 and a MAPE of 11.10%, with forecast results for February 2026 to January 2027 ranging from 1,266,330 to 1,469,176 passengers per month. For PT Angkasa Pura I Soekarno-Hatta International Airport, the SARIMA model increased forecasting accuracy to 92.45%, showing a very good level of predictive performance, while the Intervention model achieved 88.90%, showing good accuracy. The forecasting results can be used to anticipate demand surges by ensuring sufficient capacity and the availability of key facilities that determine passengers' level of service.

Keywords: Number of Departure Passengers, SARIMA, Step Function Intervention Model.

1. Introduction

The pneumonia outbreak caused by the coronavirus in Wuhan, Hubei Province, in December 2019, quickly spread throughout China and the world. This disease is known as Coronavirus Disease 2019 (COVID-19), was caused by Severe Acute Respiratory Syndrome Coronavirus-2 (SARS-CoV-2) [1]. The first case in Indonesia was confirmed in March 2020 in Depok, West Java [2]. The pandemic has significantly impacted various aspects of life, specifically the transportation sector [3]. The implementation of Government Regulation Number 21 of 2020 concerning Large-Scale Social Restrictions (PSBB) and Presidential Decree Number 12 of 2020 which designated the Covid-19 pandemic as a social disaster caused a reduction in the number of domestic passengers at Soekarno-Hatta International Airport in March 2020, the number of domestic passengers departing through Soetta Airport decreased by 21.23% compared to March 2019 and decreased

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by 84.24% in April 2020 compared to March 2020 [4]. However, at the end of 2020, the number of passengers increased by 12.38% in December compared to November [5].

The number of domestic passengers at Soekarno-Hatta International Airport showed an increase in December 2021, reaching 4.0 million or an increase of 12.29% compared to November 2021. Overall, the increase in the number of domestic passengers in 2021 was recorded at 22.29%, with a contribution of 1.2 million passengers or 29.84% of total domestic passengers [6]. According to the Flight report [7], in June 2023, the Airport was ranked 18th on the list of 100 busiest airports in the world, based on daily departure schedules. The data pattern of the number of domestic passengers showed seasonal characteristics [8]. The SARIMA method was used because it is more accurate and precise for predicting seasonal time series data [9, 10]. Meanwhile, special events or conditions that influence time series data patterns, such as natural disasters, political policies, promotions, or holidays [11]. Intervention events that change the pattern of time series data are assumed to occur at a particular time, T [12]. The COVID-19 pandemic is among the intervention factors that influence the stationarity of time series data [13]. The increase in COVID-19 cases in March 2020 prompted the implementation of a lockdown policy in Indonesia as an effort to minimize the spread of the virus [14].

The intervention analysis method is used to analyze the magnitude of the intervention effect when the implementation time is known in time series data. On the other hand, the outlier detection method is used to analyze the effects of interventions at unknown times [15, 16]. The advantage of intervention analysis is its ability to identify whether an event influences time series data with an intervention effect [17]. The intervention model was proven to be superior to the SARIMA model in predicting the number of domestic airplane passengers at Soekarno-Hatta International Airport during the COVID-19 pandemic [8]. Therefore, it is necessary to investigate whether applying the intervention model at the current point in December 2025 ($T + 70$).

In general, the forecasts provide a basis for strategic decision-making, including policy setting, strategic development planning, and operational management [18]. From a global perspective, similar studies have used intervention analysis and interrupted time series approaches to assess the effects of pandemic-related events and government policies on transportation and mobility. For example, [19] examined the impact of government policies and national holidays on COVID-19 case numbers in Iran using intervention time series models. The results showed that both policy measures and social events can trigger structural changes in temporal data.

This study aimed to obtain the best model using the SARIMA method and Step Function Intervention in predicting the number of domestic passengers at Soekarno-Hatta International Airport, based on data for the period between January 2006 and December 2025. The data showed extreme fluctuations due to the drastic decline in the number of passengers during the COVID-19 pandemic. Intervention Analysis was used because there were intervention variables that influenced the number of passengers. The intervention model was considered to be more suitable than the SARIMA model. In addition, the use of interventions in ARIMA has been proven to be able to reduce MAPE values by almost 45% [20]. Beyond reducing air passenger volumes, the COVID-19 pandemic affected Indonesia's economy. National growth slowed rapidly, with projections showing a possible contraction of -0.4 percent under the worst-case scenario [21]. The most affected sectors were households, SMEs, and finance, alongside widespread layoffs affecting over 1.5 million workers. Manufacturing and trade weakened, tourism and transport experienced heavy losses with thousands of flight cancellations, and hotel occupancy plunged by about 50 percent, while inflation rose to 2.96 percent. Overall, the pandemic disrupted nearly all economic sectors, prompting the government to respond with fiscal and monetary stimulus, including lower benchmark interest rates and expanded social assistance to preserve economic stability and support recovery.

These insights are particularly relevant to passenger traffic forecasting, where data often have strong seasonal structures and are influenced by external events such as government restrictions or public health interventions. Therefore, in this study, the classical Seasonal ARIMA and Step

Function Intervention was preferred for its interpretability, parsimony, and ability to explicitly quantify the duration and strength of intervention effects. This methodological choice provided a transparent and robust framework for understanding and forecasting passenger dynamics in response to extraordinary events such as the COVID-19 pandemic.

2. Methods

This section describes the data used in the study, the modelling framework, and the evaluation criteria employed to compare forecasting performance. The analysis was conducted using both the SARIMA model and the Step Function Intervention model to capture the seasonal pattern of passenger traffic as well as the structural change associated with the COVID-19 pandemic.

2.1. Data

The data in this study were the number of passengers departing at the Domestic Departure Terminal of Soekarno-Hatta International Airport. The data cover a monthly period starting from January 2006 to January 2026, which consisted of 241 data points. These data were obtained from the Central Statistics Agency (BPS) website [22].

Table 1: Data on the number of departing passengers at the domestic departure terminal of Soekarno-Hatta International Airport for the period January 2006 to January 2026.

Number	Year	Month	Number of Passengers
1	2006	January	1,005,200
2	2006	February	723,717
⋮	⋮	⋮	⋮
240	2025	December	1,585,607
241	2026	January	1,319,931

Source: BPS – Statistics Indonesia, 2006–2025.

There was an intervention period started in March 2020, which showed the special event due to the COVID-19 pandemic in Indonesia that affect the time series data [8].

2.2. Time-Series Modeling

This study used the SARIMA and Step Function Intervention Model. Splitting the data into two sets: the training data, which spans from January 2006 to January 2025, and testing data, which spans from February 2025 to January 2026 as test data is used for model validation. Next, before applying the Step Function Intervention method, the data were first divided based on the time the intervention occurred. The intervention in this study is the COVID-19 pandemic in Indonesia that has occurred since March 2020.

2.3. Seasonal Autoregressive Integrated Moving Average Model

The analysis stages for predicting the number of departing passengers using the SARIMA model are shown in Fig. 1(a). The first step in the analysis was to identify a model in the data on the number of departing passengers at the Domestic Departure Terminal. Data from January 2006 to January 2025 as training data is used for modeling, while data from February 2025 to January 2026 as test data is used for model validation. At this stage, the time series was analyzed to model the characteristics of the data. Furthermore, initial identification was conducted visually through data plots to observe trends, seasonal components, and non-stationarity in variance. This stage was also used to determine the preprocessing techniques needed to form stationary data. The second stage was to assess stationarity in the mean and to stabilize the variance. Mean stationarity was examined using the Augmented Dickey-Fuller (ADF) test whereas variance stabilization was addressed using the Box-Cox transformation. When the series was not stationary in the mean, differencing was applied. The transformation criterion was based on the λ value obtained from the Box-Cox plot. If $\lambda = 1$, no Box-Cox transformation was required. A second check was then carried out to ensure data stationarity. The Partial Autocorrelation Function (PACF) and Autocorrelation Function (ACF) are used to identify the SARIMA model [23]. After the appropriate model was determined, the next step was to estimate the parameters. This estimation was carried out by testing the feasibility of the SARIMA$(p, d, q)(P, D, Q)_{12}$ model. Estimates the parameters of the model using the Maximum Likelihood Estimation (MLE) method to estimate the parameters of the model [24, 25].

The SARIMA model $(p, d, q)(P, D, Q)_s$ is presented in Eq. (1) [24].

$$\phi_p(B)\,\Phi_P(B^S)\,(1-B)^d\,(1-B^S)^D X_t = \theta_q(B)\,\Theta_Q(B^S)\,e_t \tag{1}$$

where $\phi_p(B)$ is the autoregressive polynomial of order p, $\Phi_P(B^S)$ is the seasonal autoregressive polynomial of order P, $\theta_q(B)$ is the moving average polynomial of order q, $\Theta_Q(B^S)$ is the seasonal moving average polynomial of order Q, $(1-B)^d$ denotes non-seasonal differencing of order d, and $(1-B^S)^D$ denotes seasonal differencing of order D.

Model verification (diagnostics) was conducted to examine residual assumptions, such as residual independence (white noise) and normality tests based on the results of the statistical test calculations for the Ljung-Box test and the Kolmogorov-Smirnov test. When the model is correct, the predicted value (fitted value) will have similar characteristics to the original data. The residuals resulting from the fitted model should follow the error assumptions of the theoretical model, such as white noise and residual normality (although normality is less important than white noise) [26]. When these assumptions are not met, then step 2 needs to be repeated. The best model is obtained from several models that have been formed based totally on the Parsimony principle and Akaike's Information Criterion (AIC) value. The model with the smallest AIC value is the best SARIMA model [8]. Once the best model is obtained and the required assumptions are met, the model can be used to predict the number of departing passengers in the period February 2026 to January 2027, using the SARIMA$(1, 1, 1)(1, 0, 0)_{12}$ model.

2.4. Intervention Model

The stages of modelling using Intervention (Fig. 1(b)) are generally as follows. Intervention events can occur in two states based on the duration of their effect: pulse function and step function. Pulse function is an intervention with a temporary impact over a certain period, while step function has a long-term impact [16, 27]. Intervention notations for step function $\left(S_t^{(T)}\right)$ is presented in Eq. (2) [16].

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

T is the start time of the intervention event. The stages of analysis to predict the Number of Departing Passengers at the Departure Terminal using the Intervention model are shown in Fig. 1(b).

Divide the training data into two data before the intervention and the data during the intervention. Data I were training data in the pre-intervention period, where $t = 1, 2, \ldots, 170$, starting from January 2006 to February 2020. Data II were training data during the intervention starting from March 2020 to January 2025, where $t = 171, 172, \ldots, 229$.

2.4.1. SARIMA Modeling pre-Intervention

This study started with model identification based on passenger data departing at the Domestic Departure Terminal of Soekarno-Hatta International Airport from January 2006 to February 2020. The second stage was to assess stationarity in the mean and to stabilize the variance. Mean stationarity was examined using the ADF test whereas variance stabilization was addressed using the Box-Cox transformation. When the series was not stationary in the mean, differencing was applied. The transformation criterion was based on the λ value obtained from the Box-Cox plot. If $\lambda = 1$, no Box-Cox transformation was required. The PACF and ACF are used to identify the SARIMA model. The parameters were then estimated and the resulting SARIMA$(p, d, q)(P, D, Q)_{12}$ model fit was evaluated. Furthermore, verification tests were carried out by checking the independence of the residuals (white noise) and normality. When the assumptions are not met, the process is repeated, otherwise, the best model is determined. The best SARIMA model before intervention was selected based on data up to February 2020. Forecasting as much data as possible during the intervention using the SARIMA model.

2.4.2. Identification of Intervention Response

Make a graph of the residual using the best SARIMA model pre-intervention to identify the intervention order that exceeds the $\pm 3\hat{\sigma}$ limit [25]. Identify the intervention response that is the order b, s, and r based on the residual graph. Perform parameter estimation and check the significance of parameter estimates from the intervention model. The notation of the intervention model is presented in Eq. (3).

$$Z_t = f(I_t) = \frac{\omega_s(B)}{\delta_r(B)} B^b I_t + X_t \tag{3}$$

Z_t is the response variable, I_t is the intervention variable, b is the delay time or time to start the intervention effect, $\omega_s(B)$ is $\omega_0 - \omega_1 B - \cdots - \omega_s B^s$ (s shows the length of time required to stabilize), $\delta_r(B)$ is $1 - \delta_1 B - \cdots - \delta_r B^r$ (r is the pattern of intervention effects that have occurred since the intervention event time T), and X_t is the SARIMA model without intervention effects (SARIMA model pre-Intervention, January 2006–February 2020). Constants b, s, and r show the effect of the intervention, where b is the delay time, s shows the stabilization time, and r describes the pattern of the intervention effect. Model verification was carried out through residual assumption diagnostics, such as residual independence (white noise) and normality tests, using data from March 2020 to January 2025 based on the results of the statistical test calculations for the Ljung-Box test and the Kolmogorov-Smirnov test. When the assumptions are met, the Intervention model is considered suitable. This model was then used to predict the number of departing passengers from February 2026 to January 2027 with Intervention SARIMA$(0, 1, 1)(1, 0, 0)_{12}$, $b = 0$, $s = 26$, $r = 0$.

2.5. Model Accuracy Measures

This study used four measures of forecasting accuracy, the Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). Also, RMSE measures the accuracy of the model by squaring the error, dividing it by the amount of data, and then taking the root, without specific units. MAPE measures the percentage of forecast deviation by comparing the absolute difference between the original data and the forecast results, and calculating the average of the percentages [28]. The equations for RMSE and MAPE are presented in Eqs. (4) and (5) [29].

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (X_i - \hat{X}_i)^2}{n}} \tag{4}$$

$$\text{MAPE} = \frac{100\%}{n} \sum_{i=1}^{n} \left| \frac{X_i - \hat{X}_i}{X_i} \right| \tag{5}$$

where X_i denotes the actual value at time i, $\hat{X}_i$ denotes the predicted value at time i, and n denotes the total number of observations. The MAPE value was used to assess the performance of the forecasting model. The prediction accuracy criteria based on MAPE are as follows: a MAPE value between 0 and 10% indicates a very good level of prediction accuracy, between 10% and 20% indicates good accuracy, between 20% and 50% indicates reasonable accuracy, and above 50% indicates poor prediction accuracy [30].

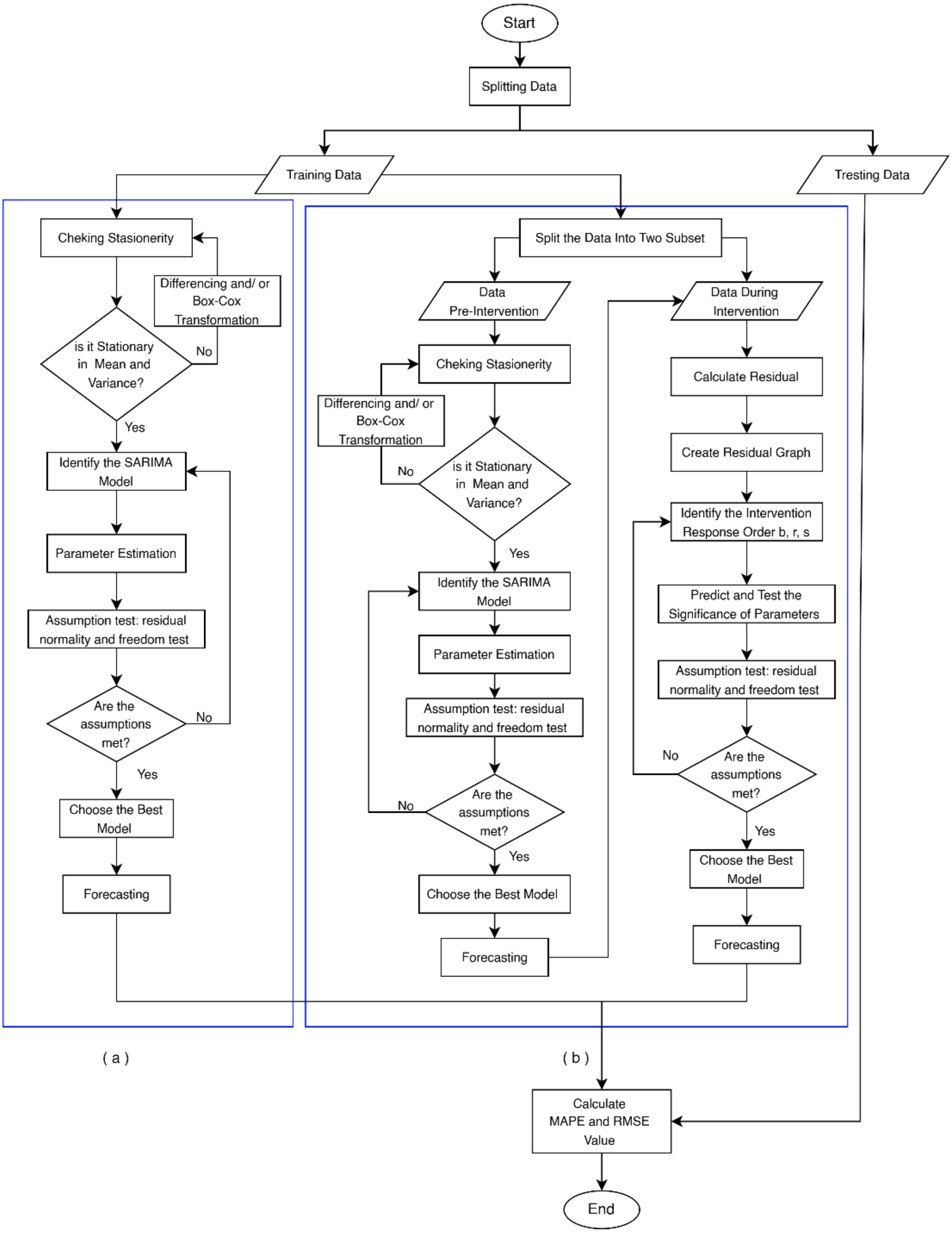

Fig. 1: Study Stages Flowchart (a) SARIMA model, (b) Step Function Intervention model (Source: Data analysis process).

3. Results and Discussion

To provide initial information, Fig. 2 shows the data used. Based on the time series graph in Fig. 2, it is obvious that the COVID-19 pandemic occurred in early 2020. This pandemic had a significant impact on flights in Indonesia, causing a drastic decline in the number of passengers in April 2020, a lower within the number of passengers by 1,020,695 human beings as compared to March 2020.

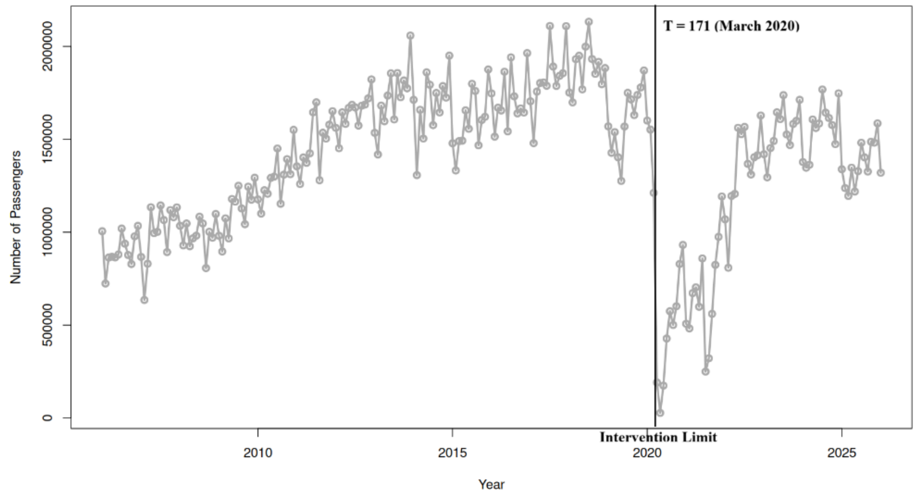

Fig. 2: Data on the number of departing passengers at the domestic departure terminal of Soekarno-Hatta International Airport for the period January 2006 to January 2026. (Source: BPS – Statistics Indonesia, 2006–2026)

3.1. Seasonal Autoregressive Integrated Moving Average

Checking Stationarity The data used to form the SARIMA model were the number of passengers departing at the Domestic Departure Terminal of Soekarno-Hatta International Airport from January 2006 to January 2025, with 231 data entries. The stationarity of the data in the mean was tested using ADF test. The results showed that the ADF value obtained failed to reject H_0 showing the data were not stationary, hence differencing was required before conducting the ADF test again to affirm the stationarity in the mean. Using a Box-Cox analysis, the estimated λ was close to 1, suggesting that the variance is already sufficiently stable, therefore no transformation was applied.

Identification of Model To identify the appropriate SARIMA model, we examine the ACF and PACF plots of the stationary data as shown in Fig. 3.

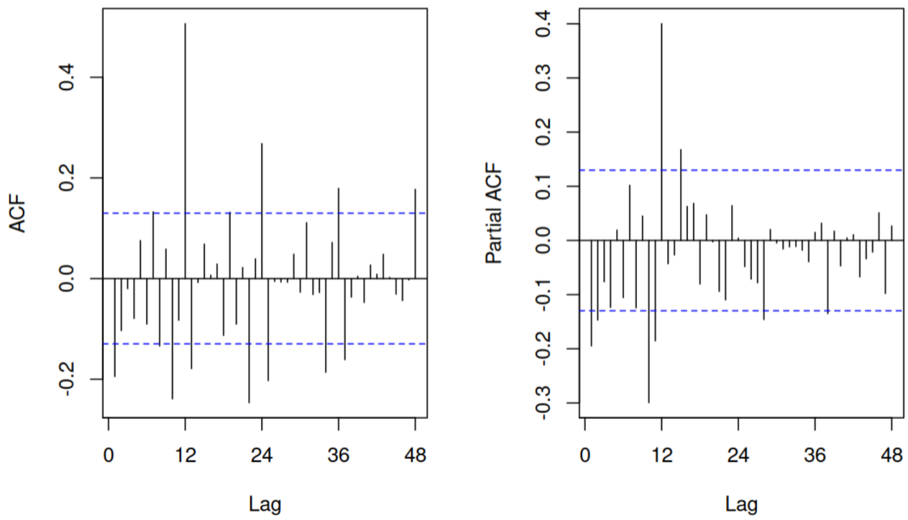

Fig. 3: Plots of (left) the autocorrelation function (ACF) and (right) the partial autocorrelation function (PACF) of the model residuals the training data.

The ACF plot shows a cut-off at lag 1 and gradually decreases at seasonal lags (12, 24, 36, and so on). The PACF plot gradually decreases at non-seasonal lags and cuts off at the first seasonal lag (lag 12). The tentative SARIMA models obtained are SARIMA$(2,1,1)(1,0,1)_{12}$, SARIMA$(1,1,1)(1,0,0)_{12}$, and SARIMA$(0,1,1)(1,0,0)_{12}$.

Parameter Estimation After identifying the three tentative models, the next step is to estimate parameters of the models. Based on information, the estimated parameters for both models are shown in Table 2.

Table 2: Estimating value of the SARIMA tentative model parameters

Model	Parameter	Estimate	p-value	AIC
SARIMA$(2,1,1)(1,0,1)_{12}$	AR(1)	0.8024	< 0.05	6122.57
	AR(2)	0.0881	0.1892	
	MA(1)	-1.0000	< 0.05	
	SAR(1)	0.5367	< 0.05	
	SMA(1)	-0.0263	0.8634	
SARIMA$(1,1,1)(1,0,0)_{12}$	AR(1)	0.8777	< 0.05	6120.3
	MA(1)	-1.0000	< 0.05	
	SAR(1)	0.5264	< 0.05	
SARIMA$(0,1,1)(1,0,0)_{12}$	MA(1)	-0.1626	< 0.05	6126.11
	SAR(1)	0.4962	< 0.05	

Table 2 shows that the models in which all parameter estimators are significant at 5% significance level are SARIMA$(1,1,1)(1,0,0)_{12}$ and SARIMA$(0,1,1)(1,0,0)_{12}$ models, because the p-value of each parameter estimator in both models are less than α (0.05), which indicates that all the parameter estimates are significant.

Model Diagnostics The next stage was the diagnostic check on the SARIMA$(1,1,1)(1,0,0)_{12}$ and SARIMA$(0,1,1)(1,0,0)_{12}$ models using the results of the statistical test calculations for the Ljung-Box test and the Kolmogorov-Smirnov test. Based on the results of the Ljung-Box test on the SARIMA$(1,1,1)(1,0,0)_{12}$ model at lag 12 yielded $X^2 = 17.633$, $df = 12$, and p-value $= 0.1273$. At the 5% significant level, H_0 was not rejected, this indicates no significant residual autocorrelation up to lag 12. Hence, the residuals are consistent with white noise with a 95% confidence level. The Ljung-Box test on the SARIMA$(0,1,1)(1,0,0)_{12}$ model at lag 12 gave p-value $= 0.09786 > 0.05$, suggesting that the residuals are not significantly autocorrelated and are consistent with white noise.

The results of the Kolmogorov-Smirnov test on the SARIMA$(1,1,1)(1,0,0)_{12}$ model showed a p-value $= 0.1011$ greater than $\alpha = 0.05$, it was concluded that the residual was normally distributed with a 95% confidence level. At the 5% significance level, the residuals on the SARIMA$(0,1,1)(1,0,0)_{12}$ model are consistent with normality, with p-value $= 0.08195 > 0.05$.

Based on the criterion of the smallest AIC, the best model is SARIMA$(1,1,1)(1,0,0)_{12}$. SARIMA$(1,1,1)(1,0,0)_{12}$ model equation is presented in Eq. (6).

$$\phi_1(B)\,\Phi_1(B^S)(1-B)X_t = \theta_1(B)e_t \tag{6}$$

The multiplication between the 1st order seasonal autoregression and the non-seasonal $d = 1$ order difference results in Eq. (7).

$$(1-0.8777B)(1-0.5264B^{12})(1-B)Y_t = (1+1.0000B)e_t \tag{7}$$

Using the SARIMA model, the training data which spans from January 2006 to January 2025, and testing data, which spans from February 2025 to January 2026 as test data is used for model validation. The forecasted monthly number of departing passengers at the domestic departure terminal of Soekarno-Hatta International Airport for February 2026 to January 2027 were: 1,269,316; 1,249,662; 1,332,382; 1,266,478; 1,326,275; 1,408,767; 1,368,535; 1,329,242; 1,415,200; 1,413,505; 1,469,362; and 1,329,338 passengers. The values of the RMSE and MAPE forecasting accuracy criteria were 115,290.6 and 7.547488%, respectively.

In addition, we conducted a comparative analysis using the SARIMA model across a different data period. The dataset used in this analysis spans January 2006 to June 2024. The training data which spans from January 2006 to June 2023, and testing data, which spans from July 2023 to June 2024 as test data is used for model validation. The forecasted monthly number of departing passengers at the domestic departure terminal of Soekarno-Hatta International Airport for January 2024 to June 2025 were: 1,643,077; 1,540,305; 1,512,589; 1,567,699; 1,576,050; 1,630,808; 1,468,155; 1,453,369; 1,461,009; 1,579,450; 1,557,168; and 1,568,882 passengers. The values of the RMSE and MAPE forecasting accuracy criteria were 106,960.9 and 5.76948%, respectively.

3.2. Step Function Intervention

This subsection describes the intervention modelling procedure used to capture the structural change in passenger volume associated with the COVID-19 pandemic. The analysis begins with pre-intervention SARIMA modelling, followed by identification of the intervention response and estimation of the final intervention model.

3.2.1. Modelling the Pre-Intervention

Checking Stationarity The first step was checking the stationarity of the data before intervention, which included the period between January 2006 and February 2020, with a total of 170 data points. In a similar way to the previous SARIMA modeling, the stationarity of the data in the mean was tested using ADF test. The results showed that the ADF value obtained failed to reject H_0 showing the data were not stationary, hence differencing was required before conducting the ADF test again to affirm the stationarity in the mean. Using a Box-Cox analysis, the estimated λ was greater than 1, suggesting that the variance is already sufficiently stable, therefore no transformation was applied.

Identification of Model To identify the appropriate SARIMA model, we examine the ACF and PACF plots of the stationary data as shown in Fig. 4.

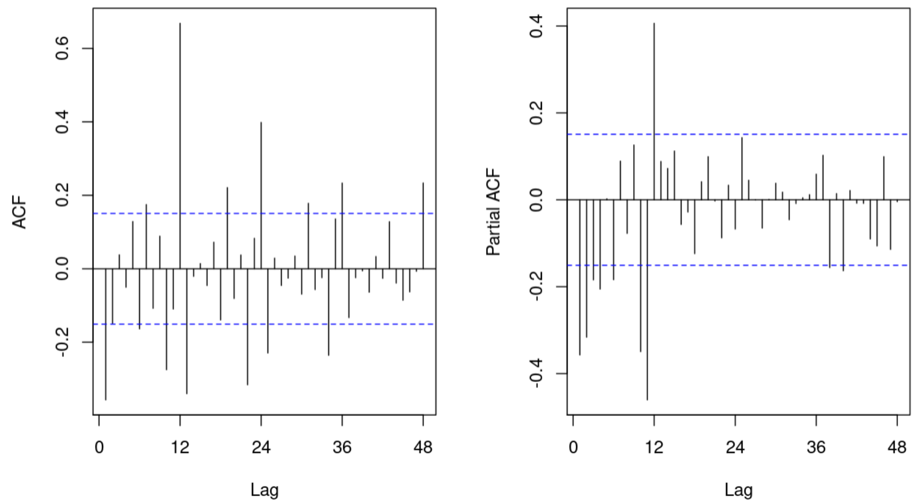

Fig. 4: Plots of (a) the autocorrelation function (ACF) and (b) the partial autocorrelation function (PACF) of the model residuals pre-intervention.

The ACF plot shows a cut-off at lag 1 and gradually decreases at seasonal lags (12, 24, 36, and so on). The PACF plot gradually decreases at non-seasonal lags and cuts off at the first seasonal lag (lag 12). The tentative SARIMA models obtained are SARIMA$(2,1,1)(1,0,1)_{12}$, SARIMA$(2,1,1)(1,0,0)_{12}$, and SARIMA$(0,1,1)(1,0,0)_{12}$.

Parameter Estimation After identifying the three tentative models, the next step is to estimate parameters of the models. Based on information, the estimated parameters for both models are shown in Table 3.

Table 3: Estimating value of the tentative model parameters SARIMA data pre-intervention

Model	Parameter	Estimate	p-value	AIC
$\text{SARIMA}(2,1,1)(1,0,1)_{12}$	AR(1)	-0.0877	0.7398	4419.93
	AR(2)	-0.0432	0.7718	
	MA(1)	-0.4570	0.0709	
	SAR(1)	0.7270	< 0.05	
	SMA(1)	-0.0895	0.5291	
$\text{SARIMA}(2,1,1)(1,0,0)_{12}$	AR(1)	0.4416	< 0.05	4417.18
	AR(2)	0.2709	< 0.05	
	MA(1)	-0.9529	< 0.05	
	SAR(1)	0.7051	< 0.05	
$\text{SARIMA}(0,1,1)(1,0,0)_{12}$	MA(1)	-0.5276	< 0.05	4414.4
	SAR(1)	0.6795	< 0.05	

Table 3 shows that the models in which all parameter estimators are significant at 5% significance level are $\text{SARIMA}(2,1,1)(1,0,0)_{12}$ and $\text{SARIMA}(0,1,1)(1,0,0)_{12}$ models, because the p-value of each parameter estimator in both models are less than α (0.05), which indicates that all the parameter estimates are significant.

Model Diagnostics The next stage was the diagnostic check on the $\text{SARIMA}(2,1,1)(1,0,0)_{12}$ and $\text{SARIMA}(0,1,1)(1,0,0)_{12}$ models using the results of the statistical test calculations for the Ljung-Box test and the Kolmogorov-Smirnov test. Based on the results of the Ljung-Box test on the $\text{SARIMA}(2,1,1)(1,0,0)_{12}$ model at lag 6 yielded $X^2 = 5.1818$, $df = 6$, and p-value $= 0.5207$. At the 5% significant level, H_0 was not rejected, this indicates no significant residual autocorrelation up to lag 6. Hence, the residuals are consistent with white noise with a 95% confidence level. The Ljung-Box test on the $\text{SARIMA}(0,1,1)(1,0,0)_{12}$ model at lag 6 gave p-value $= 0.976 > 0.05$, suggesting that the residuals are not significantly autocorrelated and are consistent with white noise.

The results of the Kolmogorov-Smirnov test on the $\text{SARIMA}(2,1,1)(1,0,0)_{12}$ model showed a p-value $= 0.0865$ greater than $\alpha = 0.05$, it was concluded that the residual was normally distributed with a 95% confidence level. At the 5% significance level, the residuals on the $\text{SARIMA}(0,1,1)(1,0,0)_{12}$ model are consistent with normality, with p-value $= 0.3183 > 0.05$.

Based on the criterion of the smallest AIC, the best model is $\text{SARIMA}(0,1,1)(1,0,0)_{12}$. The equation describing this $\text{SARIMA}(0,1,1)(1,0,0)_{12}$ model is presented in Eq. (8).

$$\Phi_1(B^S)(1-B)X_t = \theta_1(B)e_t \tag{8}$$

A multiplication between the 1st order seasonal autoregression and the non-seasonal order $d = 1$ gives Eq. (9).

$$(1-0.6795B^{12})(1-B)Y_t = (1+0.5276B)e_t \tag{9}$$

The next stage was the diagnostic check and based on the results of the statistical test calculations for the Ljung-Box test and the Kolmogorov-Smirnov test, it was concluded that the residual white noise was normally distributed.

3.2.2. Identification of Intervention Response

The initial step in identifying the intervention response is to examine residual plot of the $\text{SARIMA}(0,1,1)(1,0,0)_{12}$ model. The model residuals are obtained from the differences between the actual values from March 2020 to December 2023 and the corresponding forecast generated by the $\text{SARIMA}(0,1,1)(1,0,0)_{12}$ model, as shown in Fig. 5. The identification of the intervention response orders b, s, and r is carried out by observing the residual response pattern at the time the intervention occurs and after the intervention.

In Fig. 5, the intervention orders b, s, and r can be identified to determine the best order for constructing the intervention model. The order b represents the time delay, determined by examining the impact when the intervention begins. The order s denotes the number of time periods required for the data to return to a stable pattern. Meanwhile, the order r is determined based on whether a pattern is present in the residual plot.

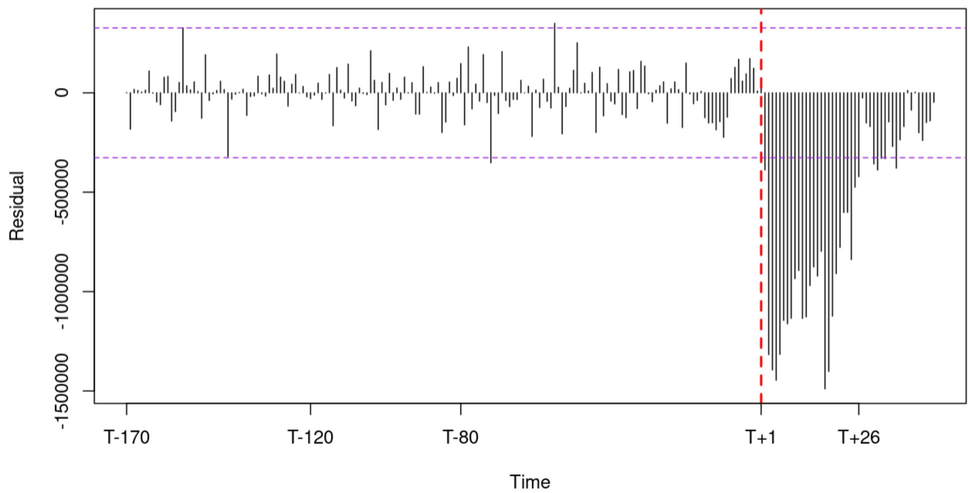

Fig. 5: Residuals Graph SARIMA Model (SARIMA$(0,1,1)(1,0,0)_{12}$).

In Fig. 5, the intervention orders b, s, and r can be identified to determine the most appropriate orders for constructing the intervention model. The order b represents the time delay, determined by observing the impact at the time the intervention begins. The order s denotes the number of time periods required for the data to return to a stable pattern. Meanwhile, the order r is determined based on whether a pattern is present in the residual plot. Based on Fig. 5, the number of passengers began to decline in March 2020, corresponding to the 171rd period ($T = 171$). This indicates that there is no time delay between the onset of the intervention effect and the time the intervention occurs. Therefore, $b = 0$. The order s is determined by the number of periods during which the passenger volume decreases before returning to its normal level. In this study, s is estimated to be 26, as indicated by residual lags in April–May 2022 that remain outside the significant bounds. The next order is r. The determination of r is based on whether a clear pattern is observed in the residual plot. The order r equals 0 if no clear pattern is present and equals 1 if a clear pattern is observed. Accordingly, the preliminary intervention model orders based on the residual plot identification are $b = 0$, $s = 26$, $r = 0$.

After identifying the two tentative models, the next step is to estimate parameters of the models. Based on information, the estimated parameters for both models are shown in Table 4.

Table 4: Estimating value of step function intervention model parameters

Model	Parameter	Estimate	p-value	AIC
	ma1	-4.9272e-01	< 0.05	
SARIMA$(0,1,1)(1,0,0)_{12}$, $b = 0$, $s = 26$, $r = 0$	sar1	5.1212e-01	< 0.05	6096.12
	ω_{26}	-9.2424e+05	< 0.05	

The p-values for the parameters of SARIMA$(0,1,1)(1,0,0)_{12}$, $b = 0$, $s = 26$, $r = 0$ model are less than α (0.05), which indicates the parameter estimates are significant. The best model is SARIMA$(0,1,1)(1,0,0)_{12}$, $b = 0$, $s = 26$, $r = 0$.

Model Diagnostics The next stage was the diagnostic check on the SARIMA$(0,1,1)(1,0,0)_{12}$, $b = 0$, $s = 26$, $r = 0$ model using the results of the statistical test calculations for the Ljung-Box test and the Kolmogorov-Smirnov test. Based on the results of the Ljung-Box test at lag 6 yielded $X^2 = 8.2905$, $df = 6$, and p-value $= 0.2176$. At the 5% significant level, H_0 was not rejected, this indicates no significant residual autocorrelation up to lag 6. Hence, the residuals are consistent with white noise with a 95% confidence level. The results of the Kolmogorov-Smirnov test showed a p-value $= 0.09614$ greater than $\alpha = 0.05$, it was concluded that the residual was normally distributed with a 95% confidence level.

Modeling based on the best Step Function Intervention SARIMA$(0,1,1)(1,0,0)_{12}$, $b = 0$, $s = 26$, $r = 0$ is presented in Eq. (10).

$$Z_t = (-924240B)\, S_t^{(171)} + \frac{(1-0.4927)e_t}{(1+0.512128B^{12})(1-B)} \tag{10}$$

with

$$S_t^{(170)} = \begin{cases} 0, & t < 171 \\ 1, & t \geq 171 \end{cases} \tag{10}$$

Using the Step Function Intervention model, the training data which spans from January 2006 to January 2025, and testing data, which spans from February 2025 to January 2026 as test data is used for model validation. The forecasted monthly number of departing passengers at the domestic departure terminal of Soekarno-Hatta International Airport for February 2026 to January 2027 were: 1,288,181; 1,266,330; 1,345,235; 1,278,599; 1,335,533; 1,414,946; 1,374,140; 1,334,419; 1,417,727; 1,415,164; 1,469,176; and 1,331,105 passengers. The values of the RMSE and MAPE forecasting accuracy criteria were 168,199.4 and 11.10%, respectively.

In addition, we conducted a comparative analysis using the Step Function Intervention model across a different data period. The dataset used in this analysis spans January 2006 to June 2024. The training data which spans from January 2006 to June 2023, and testing data, which spans from July 2023 to June 2024 as test data is used for model validation. The forecasted monthly number of departing passengers at the domestic departure terminal of Soekarno-Hatta International Airport for January 2024 to June 2025 were: 1,640,744; 1,531,884; 1,500,457; 1,561,123; 1,570,177; 1,630,171; 1,452,035; 1,435,844; 1,444,210; 1,573,922; 1,549,519; and 1,562,348 passengers. The values of the RMSE and MAPE forecasting accuracy criteria were 105,143.5 and 5.649879%, respectively.

4. Conclusion

In conclusion, based on analysis using the SARIMA and the Step Function Intervention model on data reporting the number of departing passengers at the Domestic Departure Terminal of Soekarno-Hatta International Airport from January 2006 to January 2026. Based on the criterion of the smallest AIC, the best SARIMA model is SARIMA$(1,1,1)(1,0,0)_{12}$ and the best Intervention model is SARIMA$(0,1,1)(1,0,0)_{12}$, $b = 0$, $s = 26$, $r = 0$. The SARIMA model was constructed using the training data, which spans from January 2006 to January 2025. The Intervention model was developed by incorporating the intervention effect that occurred in March 2020 ($T = 171$). Accordingly, the intervention response orders b, s, and r were identified by examining the residual response pattern at the time the intervention occurred and in the after the intervention period. The data from February 2025 to January 2026 as test data is used for model validation. Based on the test data, the SARIMA model has an RMSE value of 115,290.6 and a MAPE of 7.55%. The Step Function Intervention model has an RMSE value of 168,199.4 and a MAPE of 11.10%. This can be observed in Fig. 5, which shows that the pattern begins to stabilize from $T + 27$ until the end of the study period in December 2025 ($T + 70$), as it falls within the significant bounds of the $\pm 3\hat{\sigma}$ limit. Moreover, based on the principle of parsimony, the SARIMA model is preferable because it is simpler and more stable. Therefore, even in the absence of an intervention effect, the model is able to generate reliable forecasts. For PT Angkasa Pura I Soekarno Hatta International Airport, the SARIMA model increased forecasting accuracy to

92.45%, showing a very good level of predictive performance, the resulting forecast for February 2026 to January 2027 were: 1,269,316; 1,249,662; 1,332,382; 1,266,478; 1,326,275; 1,408,767; 1,368,535; 1,329,242; 1,415,200; 1,413,505; 1,469,362 and 1,329,338 passengers per month. While the Intervention model achieved 88.90% (showing good accuracy), the resulting forecast for February 2026 to January 2027 were: 1,288,181; 1,266,330; 1,345,235; 1,278,599; 1,335,533; 1,414,946; 1,374,140; 1,334,419; 1,417,727; 1,415,164; 1,469,176 and 1,331,105 passengers per month.

Overall, the comparison across two out-of-sample validation shows that the relative performance of SARIMA and the Intervention model is time-dependent. In Scenario A (July 2023–June 2024), the intervention effect yields a modest improvement (RMSE = 105,143.5; MAPE = 5.649879%) compared with the SARIMA model (RMSE = 106,960.9; MAPE = 5.76948%). However, in Scenario B (February 2025–January 2026), SARIMA provides substantially better forecasting accuracy (RMSE = 115,290.6; MAPE = 7.547488%) than the intervention model (RMSE = 168,199.4; MAPE = 11.10%). These findings indicate that intervention terms may be beneficial when the post-shock dynamics remain influential, whereas a parsimonious SARIMA specification can generalize more reliably once the series transitions toward a more stable seasonal autocorrelated regime. Consequently, model selection should be guided by validation sensitivity and the stability of post-intervention patterns, rather than assuming a uniformly superior approach. Accordingly, we recommend using SARIMA for operational forecasting in later, more stable periods, while intervention modelling is most useful for windows closer to the structural shock.

These results can be used for further study on time series forecasts from the SARIMA model can inform strategic decision-making at PT Angkasa Pura I Soekarno Hatta International Airport, specifically for preparing demand surges by ensuring sufficient capacity and the availability of key facilities that determine the passenger level of service (check-in counters, departure-lounge capacity, and number of gates). However, further research may be conducted to examine the impact of the intervention effect over a longer time span, until the time series pattern returns to a stable state comparable to the pre-intervention period.

CRediT Authorship Contribution Statement

Nur Faizin: Data curation, Software, Visualization, Formal analysis, Writing – original draft. Achmad Fauzan: Conceptualization, Validation, Investigation, Project administration, Writing – review and editing.

Declaration of Generative AI and AI-assisted technologies

During the preparation of this manuscript, the authors used a generative AI tool (specifically ChatGPT 5.2) solely to assist with language refinement and grammatical editing. All content consisting of the core material, analysis and interpretation was developed manually by the authors through discussion, with careful attention to accountable accuracy and academic integrity.

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Data and Code Availability

The data in this study were the number of passengers departing at the Domestic Departure Terminal of Soekarno-Hatta International Airport for the period between January 2006 and

December 2025, which consisted of 240 data points. These data were obtained from the Central Statistics Agency (BPS) website [22].

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