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Factors Affecting The Number Of Domestic Flights In Indonesia During Covid-19 Pandemic Using SARIMAX Method

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Abstract

Indonesia, which consists of thousands of large and small islands, relies heavily on-air transportation to support mobility between regions. As many as 80% of Indonesia's total air transportation passengers are domestic flight passengers. This shows how vital domestic flights are in Indonesia's air transportation system. However, in 2020, the COVID-19 pandemic had an impact that resulted in a decrease in the number of domestic flights in Indonesia. Therefore, an analysis is needed to determine the factors that affect the number of domestic flights in Indonesia. This study uses the SARIMAX method, a time series regression with the addition of seasonal factors and other variables or exogenous factors that significantly affect the model to improve the model's accuracy. Several exogenous variables are considered, including the number of operating civil aviation airports, positive daily cases of COVID-19, calendar effects during Eid al-Fitr and New Year's Day, and social restriction policies. The results showed that the number of operating airports one week before Eid al-Fitr, one week during Eid al-Fitr, one week before New Year, and Emergency PPKM significantly influenced the number of domestic flights. These variables offer pivotal insights into the influence of external factors on domestic flight patterns, exerting significant impacts on passenger travel behavior and subsequently influencing domestic flight volume. The integration of these variables in the SARIMAX model allows for a comprehensive analysis of the complex dynamics influencing domestic air travel in Indonesia. The best SARIMAX model obtained is SARIMAX $(1,1,1)(4,1,1)^7$ with a MAPE value of 5.35% and a coefficient of determination is 97%.

Keywords: SARIMAX, Domestic Flights in Indonesia, COVID-19

1. INTRODUCTION

Indonesia, which consists of thousands of large and small islands. It relies heavily on-air transportation to support regional mobility [3]. Air transportation is classified into two categories: domestic and international. 80 percent of passengers in Indonesia mostly came from domestic flights in 2019 [2]. This underlines domestic air travel's important role in Indonesia's transportation system, effectively connecting various regions. In 2020, the unprecedented COVID-19 pandemic significantly impacted various sectors, including the aviation industry. The government implemented a series of regulations restricting travel, resulting in a decrease in demand for air transportation compared to previous years. As a result of the pandemic, the number of domestic flights in Indonesia decreased by 59%, according to data from the Badan Pusat Statistik [2].

Existing research has dispersity factors affecting the number of domestic aircraft flights: the number of passengers. One study from [6] states that along with the high growth of aircraft movements, it is directly proportional to the number of passengers. However, only a few studies discuss other factors that affect the number of aircraft flights besides the number of passengers. So, this study focuses on factors other than the number of passengers. Research [5] states that the airport facility factor in airport use affects the development of air transport: the more airports that operate, the more flights. Research [4] states that the effect of calendar variations during the Eid al-Fitr holiday, a month before Eid al-Fitr, a month after Eid al-Fitr, during the New Year, and at the beginning of the year significantly affects the number of flights because many people carry out homecoming and holidays. The factor of social activity restrictions also affects the number of domestic flights. Quantitative research [7] shows that the Covid 19 pandemic with social restriction policies has an impact on temporary restrictions on the closure of domestic flight routes and international flights, thus affecting airline revenues. Meanwhile, using the SARIMAX method in case studies related to the aviation sector is based on research [8,9,12,13,14].

2. METHODOLOGY

2.1 Dataset

In this study, the samples utilized consist of daily data on the number of domestic flights in Indonesia, daily data on the number of civil aviation airports in Indonesia, and daily data on the number of positive COVID-19 cases from March 2, 2020, to December 31, 2021. The total number of study samples amounts to 670 days. The variables employed in this research encompass both dependent and independent variables, which are outlined as follows:

Table 2.1. Research Variables

Variable	Description	Unit
$\mathbf{Y_t}$	Number of Domestic Flights in Indonesia	Flights/Day
$\mathbf{X_{1,t}}$	Number of Civi l Aviation Airport Operations in Indonesia	Airports/Day
$\mathbf{X_{2,t}}$	Number of COVID-19 Positive Cases in Indonesia	Cases/Day

In addition, independent variables are also used as dummy variables in the form of the Eid al-Fitr effect, New Year effect, and Social Restriction Policy effect.

Table 2.2. Dummy Variables

Variable	Description	Unit
$\mathbf{I_{1,t}}$	One week before Eid al-Fitr	0 = Not period one week before Eid al-Fitr 1= Period one week before Eid al-Fitr

Variable	Description	Unit
$I_{2,t}$	One week during Eid al-Fitr	0 = Not period one week of Eid al-Fitr 1 = Period one week of Eid al-Fitr
$I_{3,t}$	One week after Eid al-Fitr	0 = Not period one week after Eid al-Fitr 1 = Period one week after Eid al-Fitr
$NY_{1,t}$	One week before New Year	0 = Not period one week before New Year 1 = Period one week before New Year
$NY_{2,t}$	One week of New Year	0 = Not period one week of New Year 1 = Period one week of New Year
$P_{1,t}$	Period of PSBB Occurrence	0 = Day t is not a period of PSBB occurrence 1 = Day t is a period of PSBB occurrence
$P_{2,t}$	Period of Transitional PSBB Occurrence	0 = Day t is not a period of Transitional PSBB occurrence 1 = Day t is a period of Transitional PSBB occurrence
$P_{3,t}$	Period of Strict PSBB Occurrence	0 = Day t is not a period of Strict PSBB occurrence 1 = Day t is a period of Strict PSBB occurrence
$P_{4,t}$	Period of PPKM Occurrence	0 = Day t is not a period of PPKM occurrence, 1 = Day t is a period of PPKM occurrence
$P_{5,t}$	Period of Micro PPKM Occurrence	0 = Day t is not a period of Micro PPKM occurrence, 1 = Day t is a period of Micro PPKM occurrence
$P_{6,t}$	Period of Emergency PPKM Occurrence	0 = Day t is not a period of Emergency PPKM occurrence 1 = Day t is a period of Emergency PPKM occurrence
$P_{7,t}$	Period of PPKM Level 3-4 Occurrence	0 = Day t is not a period of PPKM Level 3-4 occurrence 1 = Day t is a period of PPKM Level 3-4 occurrence

2.2 Time Series Model Identification

Autocorrelation Function (ACF) is an autocorrelation function that represents the linear relationship or correlation between time-t observations and previous observations. This function is usually used to see stability and shows a linear relationship between Y_t and Y_{t+k}. The autocorrelation function on stationary time series data is denoted by $\hat{\rho}_k$ where lag=1,2,3,...k can be defined as follows [10].

$$\hat{\rho}_k = \frac{E[(Y_t-\mu)(Y_{t+k}-\mu)]}{\sqrt{E[(Y_t-\mu)^2(Y_{t+k}-\mu)^2]}} = \frac{Cov(Y_t, Y_{t+k})}{Var(Y_t)} \tag{2.1}$$

Partial Autocorrelation Function (PACF) is a partial autocorrelation function used to know the correlation value between Y_t and Y_{t+k} after the influence of Y_{t+1}, Y_{t+2}, ..., Y_{t+k-1} is removed. This coefficient is referred to as the PACF at the kth lag and is defined by ϕ_{kk}; the function of the PACF is described as follows [10].

$$\phi_{kk} = Corr(Y_t, Y_{t+k} | Y_{t+1}, Y_{t+2}, \dots, Y_{t+k-1}) \tag{2.2}$$

In determining the order of the SARIMA model, namely AR(p), MA(q), SAR(P), and SMA(Q) on a time series data can be done by identifying the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. Here are instructions on selecting the SARIMA model shown in **Table 2.3**. for non-seasonal and seasonal orders [1].

Table 2.3. Determination of Non-Seasonal and Seasonal Model Order

Model	ACF	PACF
AR(p)	Rapid exponential decay	Cuts-off after lag p
MA(q)	Cuts off after lag q	Rapid exponential decay
AR(p) atau MA(p)	Cuts-off after lag q	Cuts-off after lag p
ARMA(p,q)	Rapid exponential decay	Rapid exponential decay
SAR(P)	Rapid exponential decay at seasonal lag	Cut-off after lag P^s
SMA(Q)	Cut-off after lag Q^s	Rapid exponential decay at seasonal lag
SAR(P) atau SMA(Q)	Cut-off after lag Q^s	Cut-off after lag P^s
SARMA(P,Q)	Rapid exponential decay at seasonal lag	Rapid exponential decay at seasonal lag

2.3 Seasonal Autoregressive Integrated Moving Average Exogenous (SARIMAX)

Autoregressive (AR) is a form of regression, but instead of relating the independent variables, it relates the previous time lag values. The AR(1) function states that only one previous value can be used as a function of the current value [10]. Autoregressive models of order p are denoted as AR(p) with p=1,2,3,...,n. The form of the time series model for Autoregressive is expressed as follows [10].

$$\phi_p(B)Y_t = a_t \tag{2.3}$$

The Moving Average (MA) model is a stationary model of time series data at the time-t observation value influenced by the previous q-order residuals which will affect the present value error. The Moving Average model with order is denoted as MA(q) with q = 1,2,3, ...,n. The form of the time series model for the Moving Average is expressed as follows [10].

$$Y_t = \theta_q(B)a_t \tag{2.1}$$

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model is the development of ARIMA models on time series data with seasonal patterns. Seasonal patterns are defined as patterns that occur repeatedly at certain intervals and are fixed in nature [12]. The SARIMA model is written as $SARIMA(p,d,q)(P,D,Q)^s$. The order (P,D,Q) is a parameter of seasonal SARIMA but is bound by the non-seasonal order (p,d,q). The period or seasonal factor that occurs is written as s. The seasonal period can be annual, monthly, weekly, or daily. The equation of the $SARIMA(p,d,q)(P,D,Q)^s$ model can be written as follows [10].

$$\phi_p(B)\Phi_P(1-B)^d(1-B)^D Y_t = \theta_q(B)\Theta_Q(B)^s a_t \quad (2.2)$$

SARIMAX is an extension of SARIMA analysis by adding other or exogenous factors [9]. The dependent factor (Y) influences the SARIMAX model in time and the independent variable (X) in the t-time. The general form of the SARIMAX model is as follows [10].

$$\phi_p(B)\Phi_P(1-B)^d(1-B)^D Y_t = \theta_q(B)\Theta_Q(B)^s a_t + \beta_1 X_{1,t} + \beta_2 X_{2,t} + \cdots + \beta_k X_{k,t} \quad (2.3)$$

3. RESULTS

Before modeling the factors affecting the number of domestic flights in Indonesia during a pandemic, descriptive analysis is carried out to provide an overview of the characteristics of developing the number of domestic flights in Indonesia.

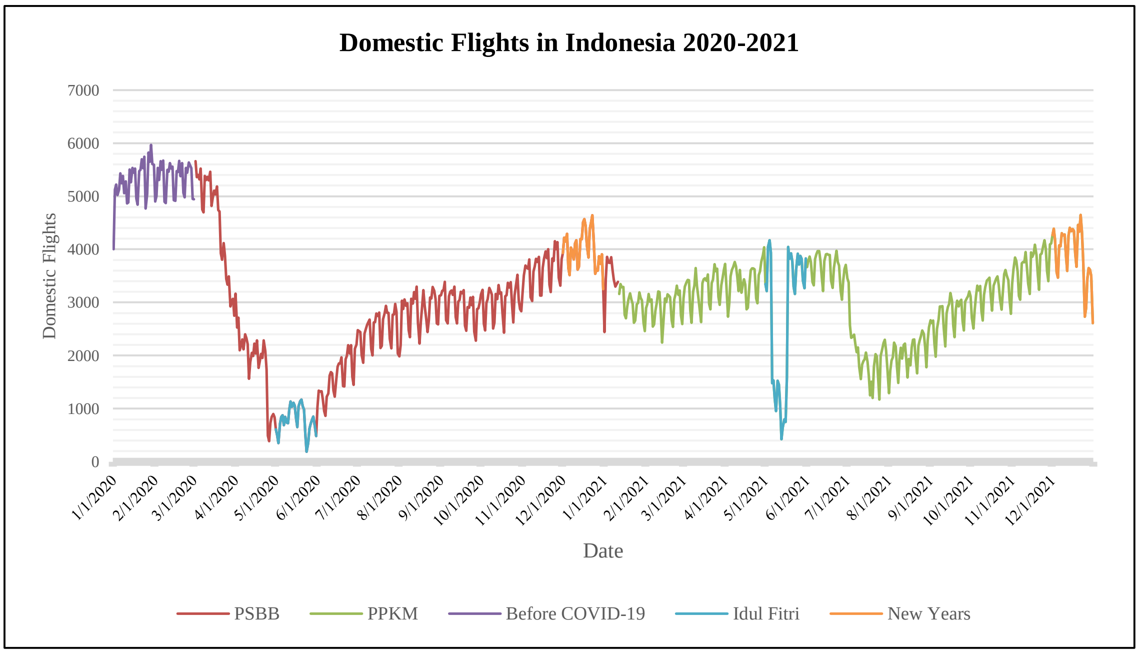

Figure 3.1. Domestic Flights in Indonesia 2020-2021

The plot shows increase and decreases in specific periods and constant increases and decreases every weekend. The pre-Covid-19 period is shown by the purple plot line from the beginning of January to the end of February. The plot shows that Indonesia's average number of daily domestic flights was 5,313. The highest number of flights occurred on 29 January 2020 at 5,967. At the time of the first entry of the COVID-19 case in Indonesia on 2 March 2020, there began a decline in the number of flights due to the implementation of the Large-Scale Social Restrictions (PSBB) policy, causing a significant decline. The orange-colored plot line shows the length of time of the PSBB. The highest decline in the number of flights reached 97 per cent by 186 flights a day, which occurred on 24 May 2020 during the Eid al-Fitr event shown by the blue plot line.

Identifying a time series model begins with identifying the characteristics of the data. One of the requirements for using the SARIMAX model is that the data must be seasonally stationary or the data pattern is distributed around the average. Since the data is not stationary, seasonal and non-seasonal 1st order differencing is Performed.

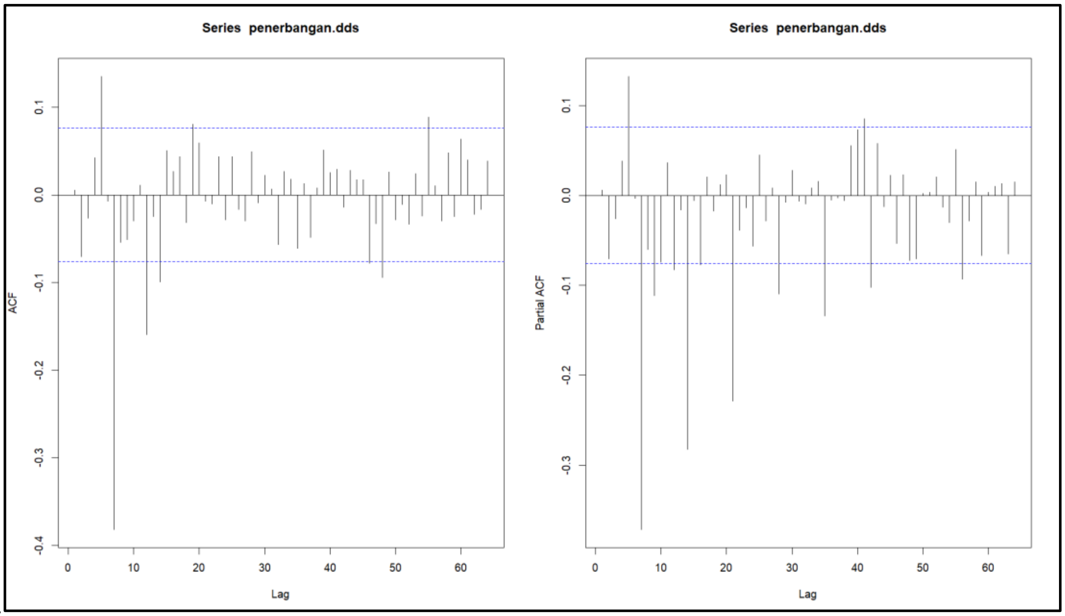

Figure 3.2. ACF and PACF Plot

Referring to **Figure 3.2.**, the non-seasonal model shows a cut-off at lag-5 on the PACF and ACF plots so that the model obtained order AR(5) and MA(5) with differentiation 1 time. Then, in the seasonal model with period 7, it can be seen that the PACF plot has a cut-off at lag-7, lag-14, lag-21, lag-28, lag-35, and lag-42 so that order 6 or SAR(6) is formed. The ACF plot has a cut-off at lag 7 and 14 so that order 2 or SMA(2) is formed. So, the model obtained is SARIMA(5,1,5)(6,1,2)^7.

From the results of the AR(p), MA(q), SAR(P), and SMA(Q) orders, a temporary SARIMA model is formed, namely SARIMA (5,1,5)(6,1,2)^7. The SARIMA (5,1,5)(6,1,2)^7 model cannot estimate parameter coefficients because the Hessian matrix used in the likelihood method is 0. Hence, there is no inverse for the data processed. Therefore, overfitting is carried out on the model so that the overfitting model results are SARIMA (4,1,5)(6,1,2)^7, SARIMA(2,1,4)(4,1,1)^7, SARIMA(3,1,1)(4,1,1)^7, SARIMA(3,1,0)(4,1,1)^7, SARIMA(2,1,0)(4,1,1)^7, SARIMA (1,1,1)(4,1,1)^7, and SARIMA (1,1,0)(4,1,1)^7. The parameter significance test will be carried out from the models formed on the independent variables. The following are the significance test values of the SARIMAX model shown in **Table 3.1 and Table 3.2.**

Table 3.1. Non-Seasonal SARIMAX Model Significance Test Results

SARIMAX	**p-value**								
	AR(1)	AR(2)	AR(3)	AR(4)	MA(1)	MA(2)	MA(3)	MA(4)	MA(5)
(4,1,5)(6,1,2)^7	0,186	0,530	0,210	0,000*	0,841	0,053*	0,025*	0,000*	0,148
(2,1,4)(4,1,1)^7	0,000*	0,000*			0,000*	0,000*	0,000*	0,013*	
(3,1,1)(4,1,1)^7	0,912	0,143	0,081		0,178				
(3,1,0)(4,1,1)^7	0,000*	0,000*	0,003*						
(2,1,0)(4,1,1)^7	0,000*	0,003*							
(1,1,1)(4,1,1)^7	0,002*				0,000*				
(1,1,0)(4,1,1)^7	0,000*								

*Parameters are significant to the model

Table 3.2. Seasonal SARIMAX Model Significance Test Results

SARIMAX	p-value							
	SAR(1)	SAR(2)	SAR(3)	SAR(4)	SAR(5)	SAR(6)	SMA(1)	SMA(2)
$(4,1,5)(6,1,2)^7$	0,000*	0,009*	0,000*	0,000*	0,129	0,980	0,639	0,000*
$(2,1,4)(4,1,1)^7$	0,017*	0,013*	0,055	0,008*			0,000*	
$(3,1,1)(4,1,1)^7$	0,019*	0,002*	0,034*	0,007*			0,000*	
$(3,1,0)(4,1,1)^7$	0,013*	0,002*	0,042*	0,008*			0,000*	
$(2,1,0)(4,1,1)^7$	0,010*	0,003*	0,042*	0,014*			0,000*	
$(1,1,1)(4,1,1)^7$	0,014*	0,002*	0,034*	0,009*			0,000*	
$(1,1,0)(4,1,1)^7$	0,012*	0,002*	0,045*	0,017*			0,000*	

*Parameters are significant to the model

The SARIMAX model is declared significant if the parameter significance test results for the SARIMAX model show model parameters with a p-value smaller than the significance level of 0.05 (5%). Models whose parameters are significant are SARIMAX (3,1,0)(4,1,1)7, SARIMAX (2,1,0)(4,1,1)7, and SARIMAX (1,1,1)(4,1,1)7, and SARIMAX (1,1,0)(4,1,1)7 Then, from the four models, the best model will be selected based on the smallest AIC value. The AIC values of the three models can be seen in **Table 3.3.**

Table 3.3. Aikake Information Criterion (AIC) Values

SARIMAX	AIC Values
SARIMAX $(3,1,0)(4,1,1)^7$	8756,872
SARIMAX $(2,1,0)(4,1,1)^7$	8763,263
SARIMAX $(1,1,1)(4,1,1)^7$	**8755,825**
SARIMAX $(1,1,0)(4,1,1)^7$	8770,689

The AIC values in **Table 3.3** show that the SARIMAX model with the smallest AIC value is the SARIMAX (1,1,1)(4,1,1)7 model. This model has the smallest AIC value of 8755.825. From this model, a significance test was conducted using all exogenous variables. The significance test results show that the variable number of positive Covid-19 cases ($X_{t,2}$), dummy variables one week after Eid al-Fitr ($I_{3,t}$), one week during the new year ($NY_{2,t}$), dummy variables when PSBB ($P_{1,t}$) Transitional PSBB ($P_{2,t}$), Tight PSBB ($P_{3,t}$), PPKM ($P_{4,t}$), Micro PPKM ($P_{5,t}$), and Level 3-4 PPKM ($P_{7,t}$) are not significant. So, it is necessary to do a backward elimination evaluation by eliminating variable variables one by one, starting from the variable with the smallest t-value or the parameter with the most insignificant p-value.

Based on the backward elimination results, the significant variables are the number of operating civil aviation airports ($X_{1,t}$), dummy variables one week before Eid al-Fitr ($I_{1,t}$), one week during Eid al-Fitr ($I_{2,t}$), one week before the new year ($NY_{1,t}$), and Emergency PPKM ($P_{6,t}$). The estimation and significance test of the SARIMAX $(1,1,1)(4,1,1)^7$ model without insignificant variables are as follows.

Table 3.4. The Estimation and Significance Test of The SARIMAX $(1,1,1)(4,1,1)^7$

Parameter	Variable	*Estimate*	*SE*	*t-value*	*p-value*
ϕ_1	AR1	0,356	0,106	3,352	0,001
θ_1	MA1	-0,624	0,086	-7,221	0,000
Φ_1	SAR1	0,098	0,040	2,440	0,015
Φ_2	SAR2	0,131	0,041	3,210	0,001
Φ_3	SAR3	0,084	0,041	2,044	0,041

Parameter	Variable	*Estimate*	*SE*	*t-value*	*p-value*
$\mathbf{\Phi_4}$	SAR4	0,105	0,041	2,552	0,011
$\mathbf{\Theta_1}$	SMA1	-1,000	0,025	-39,841	0,000
$\boldsymbol{\beta_{1,t}}$	$X_{1,t}$	18,310	0,985	18,583	0,000
$\boldsymbol{\alpha_{1,t}}$	$I_{1,t}$	-722,703	89,487	-8,076	0,000
$\boldsymbol{\alpha_{2,t}}$	$I_{2,t}$	-458,146	90,858	-5,042	0,000
$\boldsymbol{\gamma_{1,t}}$	$NY_{1,t}$	-227,371	94,208	-2,414	0,016
$\boldsymbol{\omega_{6,t}}$	$P_{6,t}$	-385,232	112,907	-3,412	0,001

From this model, the SARIMAX $(1,1,1)(4,1,1)^7$ model without insignificant variables can be systematically written as follows.

$$\begin{aligned}\hat{Y}_t = {} & \beta_{1,t}X_{1,t}, +\alpha_{1,t}I_{1,t} + \alpha_{2,t}I_{2,t} + \gamma_{1,t}TB_{1,t} + \omega_{6,t}P_{6,t} + Y_{t-1} + \phi_1 Y_{t-1} - \phi_1 Y_{t-2} \\ & + (1+\Phi_1)Y_{t-7} - (\Phi_1 - \Phi_2)Y_{t-14} - (\Phi_2 - \Phi_3)Y_{t-21} \\ & - (\Phi_3 - \Phi_4)Y_{t-28} - \Phi_4 Y_{t-35} - (1+\Phi_1)Y_{t-8} - (\Phi_2 - \Phi_1)Y_{t-15} \\ & - (\Phi_3 - \Phi_2)Y_{t-22} - (\Phi_4 - \Phi_3)Y_{t-29} + \Phi_4 Y_{t-36} - (\phi_1 + \phi_1\Phi_1)Y_{t-8} \\ & - (\phi_1\Phi_2 - \phi_1\Phi_1)Y_{t-15} - (\phi_1\Phi_3 - \phi_1\Phi_2)Y_{t-22} \\ & - (\phi_1\Phi_4 - \phi_1\Phi_3)Y_{t-29} + \phi_1\Phi_4 Y_{t-36} + (\phi_1 + \phi_1\Phi_1)Y_{t-9} \\ & - (\phi_1\Phi_1 - \phi_1\Phi_2)Y_{t-16} - (\phi_1\Phi_2 - \phi_1\Phi_3)Y_{t-23} \\ & - (\phi_1\Phi_3 - \phi_1\Phi_4)Y_{t-30} - \phi_1\Phi_4 Y_{t-37} + a_t + \Theta_1 a_{t-7} + \theta_1 a_{t-1} \\ & + \Theta_1\theta_1 a_{t-8}\end{aligned} \tag{3.1}$$

The model can be formulated as follows if the estimated values are entered.

$$\begin{aligned}\hat{Y}_t = {} & 18{,}310X_{1,t}, -722{,}7I_{1,t} - 458{,}1I_{2,t} - 227{,}4TB_{1,t} - 385{,}23P_{6,t} + Y_{t-1} \\ & + 0{,}356Y_{t-1} - 0{,}356Y_{t-2} + 1{,}098Y_{t-7} + 0{,}033Y_{t-14} - 0{,}047Y_{t-21} \\ & + 0{,}021Y_{t-28} - 0{,}105Y_{t-35} - 1{,}098Y_{t-8} - 0{,}033Y_{t-15} + 0{,}047Y_{t-22} \\ & - 0{,}021Y_{t-29} + 0{,}105Y_{t-36} - 0{,}391Y_{t-8} - 0{,}012Y_{t-15} + 0{,}017Y_{t-22} \\ & - 0{,}008Y_{t-29} + 0{,}038Y_{t-36} + 0{,}391Y_{t-9} + 0{,}012Y_{t-16} - 0{,}017Y_{t-23} \\ & + 0{,}008Y_{t-30} - 0{,}038Y_{t-37} - a_{t-7} - 0{,}624a_{t-1} + 0{,}624a_{t-8} + a_t\end{aligned} \tag{3.2}$$

Then, one of the assumptions of this analysis is that the differences are not correlated or called white noise. Testing for white noise is done using the L-Jung Box test, which aims to prove that the model does not have autocorrelation. The results of the L-Jung Box test are as follows.

Table 3.5. L-Jung Box Test Results

Model	Lag	Df	*Q*	$X^2_{\alpha;df}$	*p-value*
SARIMAX$(1,1,1)(4,1,1)^7$	14	7	12,57	14,067	0,08332
	21	14	14,5	23,684	0,4132
	28	21	18,01	32,671	0,6484

Based on the diagnostic test results, the white noise residual assumption has been met, so the SARIMAX$(1,1,1)(4,1,1)^7$ model is feasible. In addition, it can also be seen how much influence exogenous factors have on the dependent variable by using the coefficient of determination (R^2). The coefficient of determination (R^2) is 0.969 or 97%, which means that the influence given by exogenous factors, namely the number of operating civil aviation airports ($X_{1,t}$), dummy variables one week before Eid al-Fitr ($I_{1,t}$), one week during Eid al-Fitr ($I_{2,t}$), one week before the new year ($NY_{1,t}$), and Emergency PPKM ($P_{6,t}$) on the number of domestic flights in Indonesia by 97% while for 3% influenced by other factors not examined. From the best model, SARIMAX$(1,1,1)(4,1,1)^{7,}$ the error value of the predicted value against the actual value is 5.35%. This value falls into the category of high or perfect estimator accuracy.

4. CONCLUSION

The best SARIMAX model used to determine the factors affecting the number of domestic flights in Indonesia is the SARIMAX(1,1,1)(4,1,1$)^7$ model with significant variables in this model are the variable the number of operating civil aviation airports ($X_{1,t}$), dummy variables one week before Eid al-Fitr ($I_{1,t}$), one week during Eid al-Fitr ($I_{2,t}$), one week before the new year ($NY_{1,t}$), and Emergency PPKM ($P_{6,t}$). The accuracy of the model estimator using the MAPE value is 5.35%. The effect of exogenous factors on the number of domestic flights in Indonesia is 97%, while 3% is influenced by other factors that are not studied.

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