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Comparison of The SARIMA Model and Intervention in Forecasting The Number of Domestic Passengers at Soekarno-Hatta International Airport*

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The Covid-19 pandemic has had a massive effect on the air transportation sector. Soekarno-Hatta International Airport (Soetta) skilled a lower variety of passengers because of the Covid-19 pandemic, even though Soetta Airport persisted to perform normally. Forecasting the number of passengers needs to be done by the airport to decide the proper policy. Therefore, the airport wishes to estimate the range of passengers to determine the right coverage and prepare the facilities provided if there may be a boom withinside the range of passengers throughout the Covid-19 pandemic. Forecasting the number of domestic passengers at Soetta Airport on this examination makes use of the SARIMA model and intervention. This examination compares the SARIMA model and the intervention in forecasting the number of domestic passengers at Soetta Airport. The effects confirmed that the best SARIMA model became ARIMA ARIMA(0,1,0)(1,0,0)12 with MAPE and RMSE of 55.18% and 588887.4, respectively. The best intervention model became ARIMA0,1,1) (1,0,0)12 b = 0, s = 5, r = 1 with MAPE of 35.25% and RMSE of 238563.4. The MAPE and RMSE values acquired suggest that the intervention model is better than the SARIMA model in forecasting the number of domestic passengers at Soetta Airport throughout the Covid-19 pandemic.

Keywords: Covid-19, intervention, number of passengers, SARIMA.

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1. Introduction

The first case of Covid-19 in Indonesia was discovered in March 2020 (Nursofwa et al., 2020). To prevent the spread of Covid-19, the Government of Indonesia urges the public to reduce mobility and activities outside the home. This has had a considerable impact on Soekarno-Hatta International Airport (Soetta). In March 2020, the number of domestic passengers departing through Soetta Airport decreased by 21,23% compared to March 2019 (BPS, 2020). However, the airport wishes to estimate the range of passengers to determine the right coverage and prepare the facilities provided if there may be a boom withinside the range of passengers throughout the Covid-19 pandemic.

The forecasting model used for forecasting is by the data conditions. According to Fahik & Jatipaningrum (2021)., information on the number of passengers at Soetta Airport contains a seasonal pattern. Data that is influenced by seasonal factors can be modeled using the SARIMA. The SARIMA model uses past and present data from the variables to produce accurate short-term forecasts (Hyndman & Athanasopoulos, 2018a). This model requires time series data to be stationary at the mean and variance. Time series data are often changed patterns due to an event called intervention. In the data on the number of domestic passengers at Soetta Airport for January 2010 to May 2021, there is an intervention, namely Covid-19, which has occurred since March 2020 in Indonesia. According to Wei (2006), time-series data affected by the intervention can be modeled with the intervention model. The main purpose of the intervention model is to measure the magnitude and duration of the intervention effect over a time series.

Previous studies that predict the number of airplane passengers has been carried out by Durrah *et al.* (2018) and Sustrisno *et al.* (2021). (Durrah et al., 2018a) predict the number of aircraft passengers at Sultan Iskandar Muda Airport using data from 2010 to 2016 with the SARIMA model. (Sustrisno et al., 2021) predicted the number of domestic passengers at Sultan Hasanudin Airport using data from 2006 to 2018 with an intervention model. Therefore, this study will forecast the number of domestic passengers at Soetta Airport using the SARIMA model and intervention.

2. Methodology

2.1 Source of Data

The data used on this take a look at is data on the number of departures of domestic flight passengers at Soekarno-Hatta International Airport taken from the legitimate internet site of the Central Statistics Agency (BPS). The data is monthly data starting from the monthly period January 2010 to May 2021. The data for March 2020 to May 2021 is influenced by theintervention, namely Covid-19 which entered Indonesia in March 2020.

2.2 Method of Analysis

The steps taken to analyze the data in this study are as follows:

1. Conduct data exploration to see the characteristics and patterns of data
2. Divide the data into two, namely training data and test data. Data from January2010 to August 2020 as training data is used for modeling, while data

from September to May 2021 as test data is used for model validation.

3. Creating a SARIMA model
    a. Checks for stationary data.
    b. The Partial Autocorrelation Function (PACF) and Autocorrelation Function (ACF) are used to Identify the SARIMA model.
    c. Perform parameter estimation and check the significance of parameter estimators from the tentative models that have been obtained.
    d. Perform model diagnostic tests, namely freedom and normality tests of residuals.
    e. Do an overfitting model to get the best model candidate.
    f. Choose the best SARIMA model from several models that have been formed primarily based totally on the Bayesian Information Criterion (BIC) and Akaike's Information Criterion (AIC) values. The model with the smallest AIC and BIC values is the best SARIMA model.
4. Creating an intervention model
    a. Divide the training data into two data before the intervention and the data during the intervention. The intervention in this study is the Covid-19 pandemic in Indonesia that has occurred since March 2020. Hence, the data sharing is data before the intervention starting from January 2010 to February 2020 and data during the intervention starting from March 2020 to August 2020. The data before the intervention will be used to make the SARIMA data model before the intervention.
    b. Create a SARIMA model using pre-intervention data. The procedure for making the SARIMA data model before the intervention follows steps 3a to 3f.
    c. Forecasting as much data as possible during the intervention using the SARIMA model obtained in step 4b.
    d. Make a graph of the residual SARIMA data model before the intervention.
    e. Identify the intervention response that is the order b, s, and r based on the residual graph.
    f. Perform parameter estimation and check the significance of parameter estimates from the intervention model. If the parameter estimator is not significant, then return to step 4e.
    g. Perform a diagnostic check of the model, namely the test of freedom and normality of the remainder.
    h. Do overfitting by trying several other b, s, and r orders to get the best model order.
    i. Select the best intervention model from several candidate models that have been formed primarily based totally on the AIC and BIC values. The model with the smallest AIC and BIC values is the best intervention model
5. Forecasting as much as test data using the SARIMA model and the best intervention to calculate the MAPE and RMSE values in each model.
6. Comparing the forecasting results of the SARIMA model and the intervention model based on the Mean Percentage Absolute Error (MAPE) and Root Mean Square Error (RMSE) values. The model with the smallest MAPE and RMSE values is the best model for forecasting.

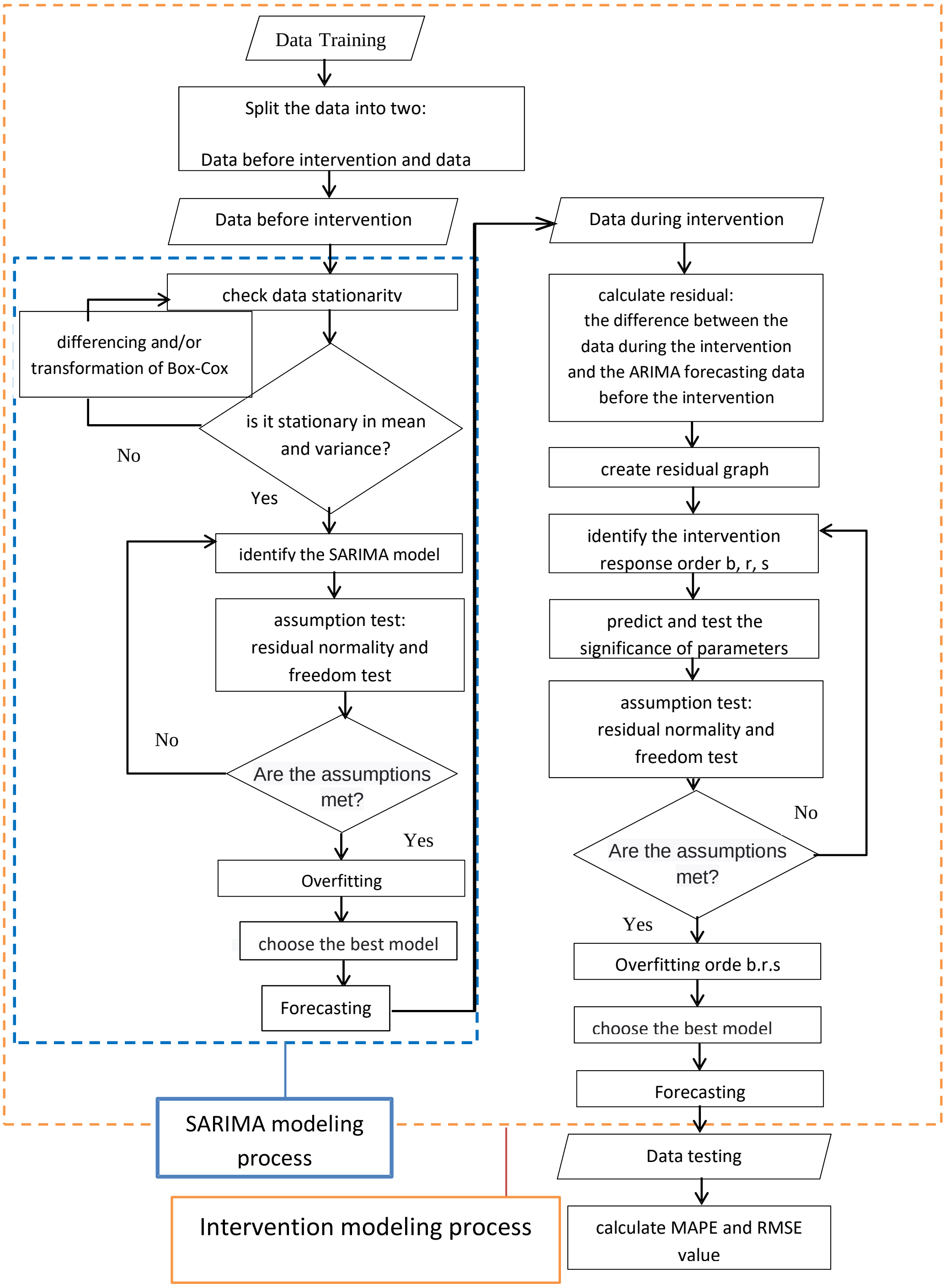

Figure 1: Flowchart of ARIMA modeling and intervention

3. Results and Discussion

3.1 Data Exploration

The results of data exploration on the number of domestic passengers at Soetta Airport show that the average number of domestic passengers departing through Soetta Airport for the period January 2010 to May 2021 is 1.520.305 people with a standard deviation of 409.449,7. The large standard deviation shows that the number of domestic passengers at Soetta Airport is quite diverse. The data plot on the number of domestic passengers shows that the data has a trend pattern and tends to fluctuate (Figure 2). The highest number of passengers occurred in July 2018 and the least in May 2020, 2.132.360 and 27.500 people, respectively. The number of domestic passengers experienced a significant decrease in April 2020, a lower withinside the number of passengers by 1.020.695 human beings as compared to March 2020. Data on the number of domestic passengers is identified as containing seasonal patterns.This can be seen by the fluctuations from month to month forming the same pattern which is repeated every 12 periods (Figure 2). During the holiday seasons, a clear seasonal pattern, such as in July and December, the number of passengers will increase, then decrease outside the holiday season.

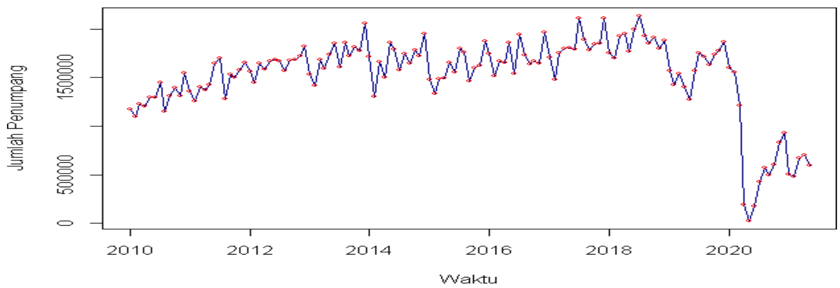

Figure 2: Plot of data on the number of departures of domestic flight passengersat Soetta International Airport

3.2 Seasonal Autoregressive Integrated Moving Average (SARIMA) Model

3.2.1 Data stationarity test

The stationary check of the data was carried out by formal exploration and testing. Explorationally, the stationarity of the data in the mean was observed from the ACF and PACF plots (Montgomery et al., 2008a). The ACF plot in Figure 3 seems to lower slowly and shape a sine wave, which means the data there may be a seasonal pattern and not stationary in the mean. The formal test used to check for stationary in the mean is the Augmented Dickey-Fuller (ADF) test (D. N. Gujarati, 2003). The ADF test results show that the p-value is more than the 5% significance level, which is 0.9421, meaning that the data is not stationary at the mean, so it is necessary to make a difference.

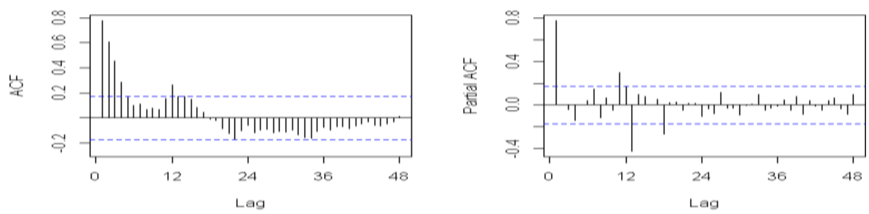

Figure 3: ACF and PACF plots of data on the number of domestic passengersat Soetta Airport which are not stationary

The ACF plot of the differentiated data indicates that the data is stationary in the mean because the ACF plot seems to decrease drastically after the 1st lag (Figure 4). Stationary examination with the ADF test on data that has undergone differentiation obtained a p-value of 0,01 or less than the 5% significance level, meaning that the data is stationary in the mean with the 1st difference (d = 1).

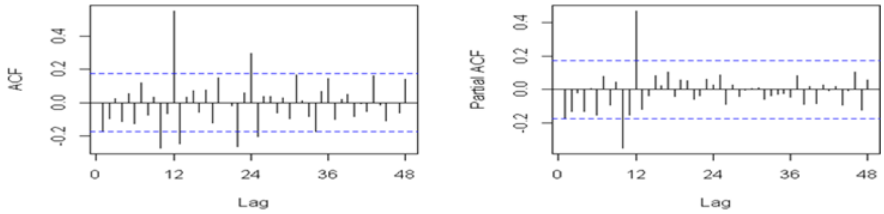

Figure 4: Plots of ACF and PACF which is already stationary

Stationary checks invariance were also carried out on data that were already stationary in the mean. Stationary examination invariance was carried out using the Box-Cox plot (WWS Wei, 2006). The lambda (λ) value obtained based on the Box- Cox plot in Figure 5 is 1,2949, which is close to the value of one or past the value of one, which indicates that the data is stationary in invariance, therefore no transformation is necessary.

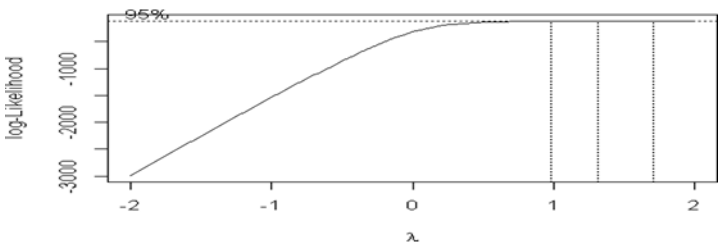

Figure 5: Plot Box-Cox data on the number of domestic passengers atSoetta Airport

3.2.2 Identify the SARIMA model (*p, d ,q*)(*P, D ,Q*)^s

The results of the identification of the PACF and ACF plots from the stationary data obtained the SARIMA tentative model which is presented in Table1. Table 1 indicates that the ARIMA(0,1,0)(1,0,0)^{12} model is significant for each parameter estimator, it can be seen from the p-value is smaller than the 5% significance level. While the ARIMA(0,1,1)(1,0,0)^{12}, and ARIMA(1,1,0)(1,0,0)^{12} models are not all significant parameter estimators at the 5% significance level.

Table 1: Estimator value of the SARIMA tentative model parameter

Model	Type	Coefficient	p-value
ARIMA(0,1,0)(1,0,0)^{12}	SAR(1)	0,6918	< 0,0001
ARIMA(0,1,1)(1,0,0)^{12}	MA(1)*	-0,1299	0,1374
	SAR(1)	0,6975	< 0,0001
ARIMA(1,1,0)(1,0,0)^{12}	AR(1)*	-0,1338	0,1294
	SAR(1)	0,6995	< 0,0001

*parameter estimator is not significant at 5% significance level

3.2.3 Model Diagnostics

The model in which all parameter estimators are significant will then be tested for model diagnostics. The results of the residual freedom test using the

Ljung-Box test on the ARIMA(0,1,0)(1,0,0)12 model in table 2 show that each residual lag tested has a p-value more than the 5% significance level, which means that there is no autocorrelation in the rest of the model.

Table 2: Ljung-Box test results on the rest of the ARIMA(0,1,0)(1,0,0)^{12} . model

Model	Lag	p-value
ARIMA(0,1,0)(1,0,0)^{12}	5	0,5219
	10	0,2436
	15	0,2744
	20	0,4823
	25	0,2341
	30	0,3832

Examination of residual normality was carried out using the Kolmogorov-Smirnov test (Daniel 1989). The results of the Kolmogorov-Smirnov test show that the remainder is not normally distributed because the p-value obtained is smaller than the 5% significance level, but it can be tolerated based on the central limit theorem (NUR LAELA Fitriani, 2011). The central limit theorem states that a distribution can be approximated by a normal distribution when the sample size is large (D. Anderson et al., 2011). This study used a sample size of 128 so that it can be said that the assumption of normality of the residuals in the ARIMA(0,1,0)(1,0,0)^{12} model has been fulfilled. The normality test of the residuals with the Q-Q plot and histogram in Figure 6 also shows that the distribution of the residuals is close to the normal distribution.

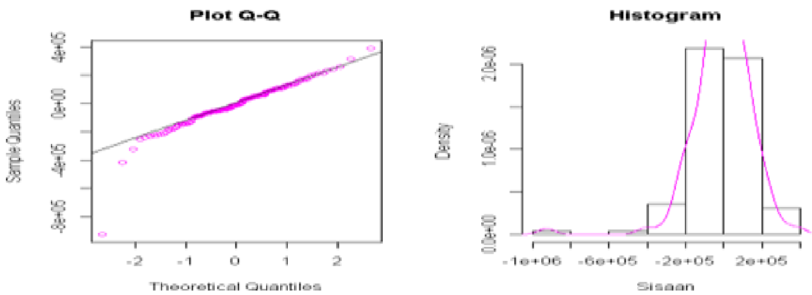

Figure 6: Plot of normal distribution of ARIMA model residual(0,1,0)(1,0,0)12

The next step is overfitting. Overfitting is done by alternately adding the order of p, q, P, and Q from the initial model to open up opportunities for a better model than the initial model identified. Table 3 shows the results of overfitting the SARIMA model.

Table 3: Estimating values of the SARIMA model parameters resulting fromoverfitting

Model	Type	Coefficient	p-value	AIC	BIC
ARIMA(0,1,0)(2,0,0)^{12}	SAR(1)	0,8139	< 0,0001	3409,30	3417,83
	SAR(2)*	-0,1655	0,1174		
ARIMA(0,1,0)(1,0,1)^{12}	SAR(1)	0,6032	< 0,0001	3409,28	3417,81
	SMA(1)*	0,1894	0,1351		

*parameter estimator is not significant at 5% significance level

The results of the model overfitting in Table 3 show that in both models, there are parameter estimators that are not significant at the 5% significance level. The SAR(1) and SMA(1) parameter estimators have a p-value greater than the 5% significance level. So primarily based totally on this case, the best SARIMA model that will be used to predict the number of domestic passengers for the next period is ARIMA(0,1,0)(1,0,0)^{12}. The equation of the model can be written as follows:

$$(1 - 0{,}6918B^{12})(1 - B)Y_t = e_t$$

3. 1 Intervention Model

3.3.1 SARIMA model data before intervention

a. Data stationarity test

The ACF plot decreases slowly (Figure 7) and the p-value of the ADF test is also more than the 5% significance level (0.1987). This indicates that the data before the intervention is not stationary at the mean, so a distinction was made to overcome it. After the 1st difference (d = 1), the data before the intervention showed stationary in the mean. The ACF plot in Figure 7 decreased drastically, and the p-value of the ADF test was smaller than the 5% significance level.

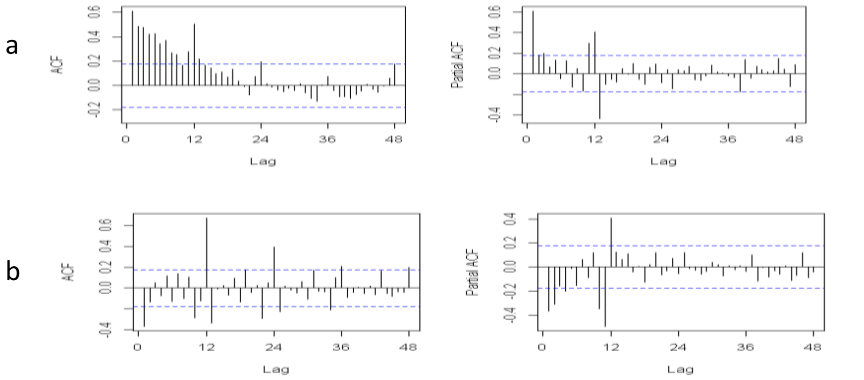

Figure 7: Plots of ACF and PACF data before intervention (a) not yet stationary in the mean and (b) already stationary in the mean

The Box-Cox plot shows that the data is stationary invariance (Figure 8). It can be seen from the lambda (λ) value which is close to one, namely 1,0743, so there is no need for transformation.

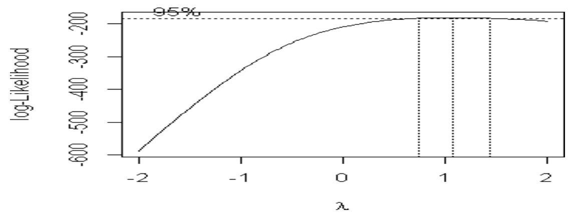

Figure 8: Box-Cox plot of data before intervention

a. Identification of ARIMA model(p,d,q)(P,D,Q)^s data before intervention

Possible tentative models based on the results of the identification of stationary PACF and ACF plots of data are ARIMA(0,1,1)(1,0,0)^{12}, ARIMA(2,1,0)(1,0,0)^{12}, and ARIMA(2,1,1)(1,0,0)^{12}. Table 4 shows that the models in which all parameter estimators are significant at 5% significance level are ARIMA(0,1,1)(1,0,0)^{12} and ARIMA(2,1,0)(1,0,0)^{12} models, because the p-value of each parameter estimator is more than the 5% significance level.

Table 4: Estimating values of the tentative model parameters Seasonal ARIMAdata before intervention

Model	Type	Coefficient	p-value
ARIMA(0,1,1)(1,0,0)^{12}	MA (1)	-0,5145	< 0,0001
	SAR(1)	0,6980	< 0,0001
ARIMA(2,1,0)(1,0,0)^{12}	AR(1)	-0,5103	< 0,0001
	AR(2)	-0,1817	0,0424
	SAR(1)	0,7109	< 0,0001
ARIMA(2,1,1)(1,0,0)^{12}	AR(1)*	-0,0795	0,8414
	AR(2)*	-0,0020	0,9928
	MA(1)*	-0,4532	0,2421
	SAR(1)	0,7032	< 0,0001

**parameter estimator is not significant at 5% significance level

b. Model diagnostics

Ljung-Box check suggests that the p-value of every residual lag withinside the ARIMA(0,1,1)(1,0,0)12 and ARIMA(2,1,0)(1,0,0)12 model is greater than the 5% significance level. which means that there is no residual autocorrelation in each models and the Kolmogorov-Smirnov test shows that the residuals of the ARIMA(0,1,1)(1,0,0)^{12} and ARIMA(2,1,0)(1,0,0)^{12} model is not normally distributed. However, based on the central limit theorem, this can be tolerated, which states that a distribution may b approximated by a normal distribution when the sample size is large (D. Anderson et al., 2011). In this study, a sample size of 122 was used, so it can be said that the assumption of normality of the residuals in both models has been fulfilled. Choose the best tentative model from the two models based on the smallest BIC and AIC values (Montgomery et al., 2015b).

Table 5: AIC and BIC values of the SARIMA tentative model data beforeintervention

Model	AIC	BIC
ARIMA(0,1,1)(1,0,0)^{12}	3174,30	3182,69
ARIMA(2,1,0)(1,0,0)^{12}	3177,45	3188,63

Table 5 shows that the best tentative model is ARIMA(0,1,1)(1,0,0)^{12} because ithas the smallest BIC and AIC values, 3174,30 and 3182,69, respectively. The results of the overfitting of the SARIMA model can be seen in Table 6.

Table 6: Estimating value of SARIMA model parameters data beforeintervention results in overfitting

Model	Type	Coefficient	p-value	AIC	BIC
ARIMA(0,1,2)	MA(1)*	-0,5329	< 0,0001		
$(1,0,0)^{12}$	MA(2)	0,0401	0,6720	3176,13	3187,31
	SAR(1)*	0,7033	< 0,0001		
ARIMA(1,1,1)	AR(1)	-0,0762	0,6722		
$(1,0,0)^{12}$	MA(1)*	-0,4564	0,0050	3176,13	3187,31
	SAR(1)*	0,7031	< 0,0001		
ARIMA(0,1,1)	MA(1)*	-0,5145	< 0,0001		
$(2,0,0)^{12}$	SAR(1)*	0,6979	< 0,0001	3176,30	3187,49
	SAR(2)	0,0002	0,9982		
ARIMA(0,1,1)	MA(1)*	-0,5146	< 0,0001		
$(1,0,1)^{12}$	SAR(1)*	0,6982	< 0,0001	3176,30	3187,49
	SMA(1)	-0,0003	0,9985		

*parameter estimator is not significant at 5% significance level

The results of the overfitting in Table 6 show that there is no model in which all parameter estimators are significant at the 5% significance level. Therefore, the best model for SARIMA data before intervention is ARIMA$(0,1,1)(1,0,0)^{12}$. The ARIMA$(0,1,1)(1,0,0)^{12}$ model is then used to forecast the number of passengers at the time of the intervention (n = 6). The ARIMA model equation$(0,1,1)(1,0,0)^{12}$ can be written as follows:

$$(1 - 0{,}6981\,B^{12})(1 - B)Y_t = (1 + 0{,}5146B)e_t$$

3.3.1 Identification of Intervention Response

The plot of the intervention pattern in Figure 9 shows that the presence of Covid-19 causes sudden and permanent changes in time series data, indicating that the intervention occurred using the step function (Yaffee & McGee, 2000).

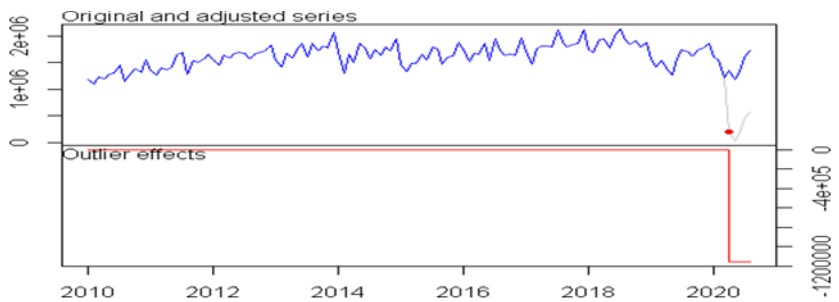

Figure 9: Plot of intervention pattern

Identification of intervention responses, namely b, s, and r, can be done by observing the graph of the rest of the ARIMA model$(0,1,1)(0,0,0)^{12}$ (Figure 10). The number of passengers began to decline based on Figure 10 was in March 2020 or the 123 rd period (T = 123). It shows no time delay between the start of the intervention effect and the time the intervention occurs so that the order b is worth 0. The order s is decided by the number of periods the number of passengers descends before returning to normal. Order s is estimated to be worth 5. It can be seen from April–August 2020, the remaining lag is still out of significant limits. The next order is the order r. Determination of order of r is seen from the presence or absence of a clear pattern on the residual graph. The order of r will be 0 if there is no clear pattern on the residual graph and 1 if the residual graph has a clear pattern. Therefore, the tentative order of the intervention model is based on the identification results of the residual graph, namely b = 0, s = 5, r = 0 and b = 0,s = 5, r = 1.

Figure 10: ARIMA model residual graph $(0.1,1)(1,0,0)^{12}$

The results of the parameter estimation of the intervention model are shown in Table 7. The intervention model in which all parameter estimators are significantat the 5% significance level is the intervention model with the orde b = 0, s = 5, and r = 1. It can be seen from the p-value of each parameter estimator is greater than the 5% significance level.

Table 7: Estimating value of intervention model parameters

Model	Type	Coefficient	*p-value*
	MA(1)	0,4893	< 0,0001
	SAR(1)	0,7021	< 0,0001
$ARIMA(0,1,1)(1,0,0)^{12}$ b = 0, s = 5, r = 0	ω_0	-862036,8	< 0,0001
	ω_5*	-170693,4	0,2305
	MA(1)	0,5475	< 0,0001
	AR(1)	0,7200	< 0,0001
$ARIMA(0,1,1)(1,0,0)^{12}$ b = 0, s = 5, r = 1	ω_0	-698034,2	< 0,0001
	ω_5	-328056,0	0,0177
	δ_0	0,5631	< 0,0001

*parameter estimator is not significant at 5% significance level

The Ljung-Box test results in Table 8 show that the $ARIMA(0,1,1)(1,0,0)^{12}$ b = 1, s = 5, r = 1 model has no autocorrelation on the remainder the p-value of each residual lag tested is more than the 5% significance level. The Kolmogorov-Smirnov test results obtained a p-value is > 0,1500, meaning that the rest of the model is normally distributed.

Table 8: Ljung-Box test results on the rest of the intervention model

Model	lag	p-value
ARIMA(0,1,1)(1,0,0)^{12} b = 0, s = 5, r = 1	6	0,9185
	12	0,6058
	18	0,7256
	24	0,4373

To get the best intervention model, several other intervention orders were also tried. The results of overfitting the intervention model in Table 9 show that the two intervention models with the results of overfitting meet the assumptions of independence and normality of waste.

Table 9: Intervention model of overfitting results on data on the number of departures of domestic passengers at Soetta Airport

Order	Ljung-Box Test	Kolmogorov-Smirnov. test
b = 0, s = 4, r = 1	There is no autocorrelation	Normal distribution
b = 0, s = 3, r = 1	There is no autocorrelation	Normal distribution

Furthermore, the best intervention model will be determined from several candidate models formed by looking at the smallest BIC and AIC values. The following compares the AIC and BIC values from the mode identification results in Table 10. Table 10 shows that the best intervention model is ARIMA(0,1,1)(1,0,0)^{12} b = 0, s = 5, r = 1 because it has a value with AIC value and Smallest BIC.

Table 10: AIC and BIC values from candidate intervention models

Model	AIC	BIC
ARIMA(0,1,1)(1,0,0)^{12} b = 0, s = 5, r = 1	3223,19	3237,21
ARIMA(0,1,1)(1,0,0)^{12} b = 0, s = 4, r = 1	3244,48	3258,55
ARIMA(0,1,1)(1,0,0)^{12} b = 0, s = 3, r = 1	3267,56	3281,66

ARIMA(0,1,1)(1,0,0)^{12} b = 0, s = 5, r = 1 intervention model will be used to predict the number of domestic passengers in the next period. The ARIMA model equation(0,1,1)(1,0,0)^{12} b = 0, s = 5, r = 1 can be written as follows:

$$Z_t = \frac{(-698034{,}2 + 328056{,}0\mathrm{B})}{(1 - 0{,}5631B)} S_t^{(123)} + \frac{(1 + 0{,}5475\mathrm{B})e_t}{(1 - 0{,}7200\, B^{12})(1 - B)}$$

dengan $S_t^{(123)} = \begin{cases} 0, t < 123 \\ 1, t \geq 123 \end{cases}$

3. 4 Forecasting

Model validation was carried out to compare the accuracy of the forecasting results of the SARIMA and the intervention model in predicting number of departures of domestic passengers at Soetta Airport. Model validation is carried out by forecasting the number of departures of domestic passengers at Soetta Airport from September 2020 to May 2021 using the SARIMA model and the best intervention. The forecasting results of the two models can be seen in Table 11.

Table 11: Results of forecasting test data using the SARIMA model and the bestintervention model

Periode	Forecast		Current
	SARIMA Models	Intervention Model	
September 2020	516.260	676.359	499.930
October 2020	591.149	845.796	600.861
November 2020	619.021	926.327	828.148
December 2020	682.131	1.021.022	928.922
January 2021	495.702	843.333	507.262
February 2021	462.064	817.524	482.132
March 2021	226.678	1.080.281	672.107
April 2021	-479.399	631.340	703.135
May 2021	-592.504	674.632	598.615
MAPE	55,18%	35,25%	
RMSE	588887,4	238563,4	

The forecasting accuracy of the two models is calculated based on the MAPE, RMSE, and correlation values. Table 11 shows that the intervention model has smaller RMSE and MAPE values than the SARIMA model. In addition, the correlation value between the actual data and the forecasted data from the intervention model is greater than the forecasted data from the SARIMA model, which are 0,50 and 0,11, respectively. It shows that the accuracy of the intervention model in forecasting the number of passengers is better than the SARIMA model in predicting the number of passengers.

Plot of the results of forecasting the number of departures of domestic passengers at Soetta Airport with the SARIMA model has a downward trend (Figure 11). The data plot of the SARIMA model forecasting results also shows a negative value in the period April and May 2021, which means that it is predicted that there will be no domestic passengers departing through Soetta Airport in that period. Meanwhile, the data plots resulting from forecasting the number of passengers using the intervention model, although not close together, appear to have the same pattern as the actual data plots.

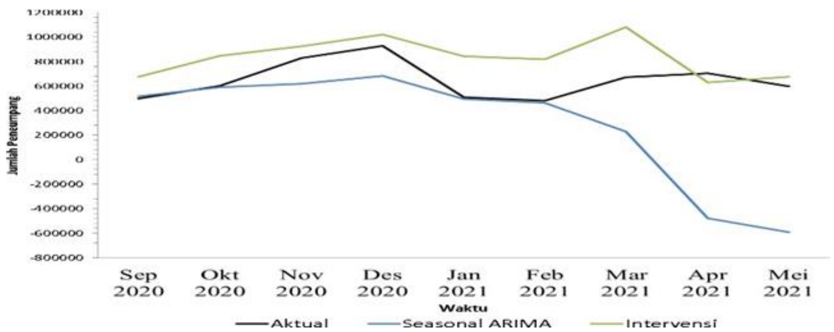

Figure 11: Plot of test data and forecasting data using the SARIMA model andintervention model

4. Conclusions and suggestions

4.1 Conclusion

Forecasting data on the number of domestic passengers at Soetta Airport can be modeled using the SARIMA and intervention models. ARIMA(0,1,0)(1,0,0)^{12} is the best SARIMA model and ARIMA(0,1,1)(1,0,0)^{12}b = 0, s = 5, r = 1 is the model best intervention. The SARIMA model shows that the number of domestic passengers at Soetta Airport is influenced by the number of domestic passengers in the previous one month, 12 months, and 13 months. The intervention modeling that is formed shows that the number of domestic passengersat Soetta Airport is influenced by the number of domestic passengers in the previous one month, two months, 12 to 14 months, and the remainder in the previous one month two months. The SARIMA model has a MAPE value of 55,18% and an RMSE of 588887,4. The intervention model has a MAPE value of 35,25%and an RMSE of 238563,4. The MAPE and RMSE values of the intervention model are smaller than the SARIMA model, so the Intervention model is better used in forecasting the number of domestic passengers at Soetta Airport during the Covid pandemic.

4.2 Suggestion

The intervention model discussed in this study is only a single-step function intervention model. In addition, to get better forecasting results, it is also possible to check and handle outliers in the data. The author also suggests adding data to get more accurate forecasting results.

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