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SARIMA INTERVENTION AND LSTM MODEL COMPARISON ANALYSIS FOR FORECASTING THE NUMBER OF FOREIGN TOURIST ARRIVALS TO BALI

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Abstract

Bali is one of the provinces that contributes significantly to Indonesia's foreign exchange earnings in the tourism sector. The COVID-19 pandemic has led to a drastic decline in the number of foreign tourists visiting Bali for over a year. Forecasting foreign tourist arrivals is one of the strategies that can serve as a guideline in formulating destination tourism policies. This research compares SARIMA and intervention models in forecasting the number of foreign tourist arrivals in Bali. The data used covers monthly foreign tourist visits to the Bali Province from January 2009 to September 2023. The results showed that the ARIMA(1,1,0)(0,1,1)^{12} model was the best SARIMA model with a MAPE of 28.8%. The best intervention model obtained is ARIMA(0,1,2)(2,1,0)^{12} b = 0, s = 3, r =1 with a MAPE of 18.67%, and the LSTM model (epoch = 50) with a MAPE of 11.74%. The LSTM model is better than the SARIMA model and the intervention model in predicting the number of foreign tourists coming to Bali based on the MAPE value obtained.

Keywords: *COVID-19, interventions, LSTM, passanger numbers, SARIMA*

INTRODUCTION

Bali is famous for its rich and unique culture and nature. Bali is one of the provinces with the best tourist destinations in the world. The beauty of Bali amazes foreign tourists, even Bali has a tourism tagline called BALI The Island of God (Putra 2018). The development of Bali in the tourism sector, facilities, and infrastructure that is increasingly accelerating makes foreign tourists have many choices in enjoying life and vacation in Bali. The *Badan Pusat Statistik* (BPS) through its publication shows the trend of the number of foreign tourists entering Bali will continue to increase until 2020. Recorded in February 2020, The number of foreign tourists visiting Bali was 364.639 visitors (BPS 2023). Then came the COVID-19 outbreak, precisely on March 16, 2020 there was a total lockdown in Indonesia so that there were no foreign activities in Indonesia to prevent transmission of COVID-19.

COVID-19 has made Bali experience a drastic decline in the number of foreign tourists for more than a year, to be precise from March 2020 to March 2022. During that period, only a few people were allowed to enter the province of Bali, and even no foreign visitors entered Bali at all. However, after the COVID-19 pandemic began to subside and the government allowed foreign visits again, tourist arrivals instantly jumped up dramatically with the last number of visitors in September 2023 recorded at 508.350, higher than the period before COVID-19 (BPS 2023). The imbalance in the number of visitors before, during, and after COVID-19 has made the province of Bali mobilize a special strategy in restoring its economy and tourism sector.

Aribowo *et al.* (2018) stated that the tourism sector is one of the main foreign exchange contributors in Indonesia. The great influence of the tourism sector on the economy in Indonesia not only generates foreign exchange, but can also expand employment opportunities (Mudrikah *et al.* 2014). Not only contributing to the Indonesian tourism economy sector, but the contribution of a number of local communities to the regional economy that helped reduce unemployment and encourage community creativity to attract crowded tourism (Mulyana *et al.* 2017). Developed and developing countries tend to prioritize the tourism sector in contributing to foreign exchange. The number of foreign tourists coming to Indonesia has a big impact on tourism investments such as hotels and restaurants. (Fairuuz *et al.* 2022).

Forecasting foreign tourist arrivals is one of the strategies that can serve as a guide in making tourist destination policies and minimizing investment uncertainty and risk (Darma *et al.* 2020). This is important because Bali is one of the provinces that contributes the largest foreign exchange in Indonesia (Sutrisnawati *et al.* 2021).

Three previous studies related to forecasting using the Seasonal Auto Regressive Integrated Moving Average (SARIMA), SARIMA intervention, and Long Short-Term Memory (LSTM) methods have been conducted by Supriatna *et al.* (2019), Christie *et al.* (2022), and Nurhambali (2023). The first study used data on the development of incoming tourists from Husein Sastranegargini Airport and Muara Jati harbor in the period January 2012 to November 2016 with the SARIMA $(4,0,0)(0,0,1)^{12}$ model resulting in a prediction error Mean Average Percentage Error (MAPE) value of 18.56. Furthermore, the second study with data on the number of visitors at the Londa tourist attraction in North Toraja to predict the number of visitors to the Londa tourist attraction from December 2021 to June 2022, the best model obtained is SARIMA $(1,1,0)(1,1,0)^6$ with an intervention order of $s = 5$, and $r = 2$ resulting in a MAPE value of 4.38%. Meanwhile, in the third study with daily gold price data from January 1, 2003 to January 20, 2023 with the best model obtained through the use of an epoch 100 optimizer which produces a MAPE value of 12.41%. Therefore, the purpose of this study is to compare forecasting models between the SARIMA Intervention and LSTM models on the number of foreign tourists to Bali before COVID-19 and after COVID-19.

This research objetives are to determine the best forecasting model to forecast the number of foreign tourists to Bali before COVID-19 and after COVID-19 using SARIMA intervention, and LSTM modeling then comparing the best SARIMA intervention and LSTM models in forecasting data on the number of foreign tourists to Bali.

METHODOLOGY

Data

The data used is data on foreigner tourist arrivals in Bali Province for the monthly period from January 2009 to September 2023. The data used is secondary data sourced from the bps.go.id website, consisting of 177 rows and 2 columns.

Data Analysis Procedure

1. Data Exploration

   Exploration of the data on the number of foreigner tourist to Bali is done by plotting time series data and seasonal data plots to determine the pattern and characteristics of the data.
2. Data Splitting

   Data from January 2009 to October 2022 serves as training data, while data from November 2022 to September 2023 serves as test data.
3. Perform SARIMA Modeling

   SARIMA modeling stages are as follows:

   Data stationarity checks are both exploratory and formal tests. Exploratory data stationarity testing uses time series data plots and Autocorrelation Function (ACF) plots. The formal test for data stationarity uses the Augmented Dickey-Fuller (ADF) test (Ruhiat *et al.* 2022).

   Handling data non-stationarity. Perform differencing if not yet stationary in average and Transformation if not yet stationary in variety. Time-series data or time series data is said to be stationary if the average, variance, and covariance at each lag remain the same at any time, if it does not meet these criteria it can be said that the data is not stationary (Aktivani 2021). According to Efendi and Soetopo (2016), data can also be said to be stationary if the data pattern is at equilibrium around a constant mean value and variance around that average is constant over a period of time. Stationarity in data is needed in time series regression analysis because it can minimize model error. Stationary variance is the variance of data that is not affected by the time series. If the data is not stationary in variance, should be transformed to make the variance more constant. Box-Cox transformation is one of the methods to stationary data that is not stationary in variety. Mathematically formulated as follows (1)

$$T(Z_t) = \begin{cases} Z_t^{(\lambda)} = \dfrac{Z_t^{(\lambda)} - 1}{\lambda}, & \lambda \neq 0 \\ \log Z_t, & \lambda = 0 \end{cases} \tag{1}$$

Description:

$T(Z_t)$: transformation data
Z_t : observation value at time t
λ : transformation parameter value

The average data is said to be stationary if fluctuates around a line parallel to the time axis (t) or around a constant average value. Data that are not stationary on average must be differentiated. In general, d-order differencing is formulated as follows (2)

$$\nabla^d = (1 - B)^d Z_t \tag{2}$$

Description:

∇ : differencing
Z_t : observation value at time t
d : order d
B : reverse operation $B^d Z_t = Z_{t-d}$

Model Identification

The model identification stage is used to estimate the model order that is suitable (tentative) through the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) forms of the stationary data. ACF is the correlation between Z_t and Z_{t+k} of same process and are separated by time lag k. The equation of covariance between Z_t and Z_{t+k} is formulated as follows (3)

$$\gamma_k = cov(Z_t, Z_{t+k}) = E(Z_t - \mu)(Z_{t+k} - \mu) \tag{3}$$

And the correlation between Z_t and Z_{t+k} is formulated as follows (4)

$$\rho_k = \frac{cov(Z_t, Z_{t+k})}{\sqrt{var(Z_t)}\sqrt{var(Z_{t+k})}} = \frac{\gamma_k}{\gamma_0} \tag{4}$$

Note :

$$var(Z_t) = var(Z_{t+k}) = \gamma_0$$

γ_k = auto-covariance function

ρ_k = ACF is analysis *time-series*

PACF is used to measure the degree ofassociation between the Z_t and Z_{t+k} when the effect of the time lag is considered separately. PACF is a function that shows the degree of partial correlation between observations at time t (denoted by Z_t) and observations at previous times ($Z_{t-1}, Z_{t-2}, \ldots, Z_{t-k}$). Equation of PACF between Z_t and Z_{t+k} as follows (5)

$$\rho_k = \frac{cov\,[(Z_t - \widehat{Z_t}),(Z_{t+k} - \widehat{Z_{t+k}})]}{\sqrt{var\,(Z_t - \widehat{Z_t})}\sqrt{var\,(Z_{t+k} - \widehat{Z_{t+k}})}} = \phi_{kk} \tag{5}$$

Efendi and Soetopo (2016) have introduced a more efficient method to solve the equation (6).

$$\phi_{kk} = \frac{\rho_k - \sum_{j=1}^{k-1} \phi_{k-1,j}\,\rho_{k-1}}{1 - \sum_{j=1}^{k-1} \phi_{k-1,j}\,\rho_j} \text{ where } \phi_{kj} = \phi_{k-1,j} - \phi_{kk}\phi_{k-1,k-j}\,, \tag{6}$$

For j = 1,2,…,k-1

Model Parameter Estimation

The SARIMA model obtained will be tested for parameter significance. Models whose parameters are insignificant are declared unfit for use, so they need to be eliminated (Ruhiat and Effendi 2018). A good model is a model that shows significant parameter estimates different from zero (Rahmalina and Novreta 2020).

Model Selection

Selection of the best SARIMA model candidate by comparing the lowest Akaike Information Criterion (AIC) value and overall significant parameter. According to Montgomery *et al.* (2015), the AIC formulation is presented in equation (7).

$$AIC = ln\left(\frac{\sum_{t=1}^{T} e_t^2}{T}\right) + \frac{2P}{T} \tag{7}$$

Description:

$\sum_{t=1}^{T} e_t^2$: sum of squares of residuals

T : number of observations

P : number of parameters

Diagnostic Check of The Feasibility of the Best Model

Diagnostic testing of the residuals of the best model obtained. A good model and kayak is a model that has mutual independence with the Ljung-Box test, residual sispread normally with the Jarque-bera test (Montgomery et al. 2015).

Perform Forecasting using Best Model

A measure of forecasting accuracy can use the Mean Absolute Percentage Error (MAPE) value benchmark (Iswari *et al.* 2022). The smaller the MAPE value indicates that the model forecasting results are closer to the actual value. The MAPE formula is as follows (Montgomery *et al.et* 2015). The MAPE value interval as a measure of the ability of the model to perform forecasting is shown in Table 1.

Table 1. A measure of the ability of the forecasting model

MAPE Range	Significance
<10%	Excellent forecasting capabilities
10%-20%	Good forecasting capabilities
20%-50%	Viable forecasting capability
>50%	Poor forecasting ability

Source : Nabillah and Ranggadara (2020)

4. Creating an intervention model
   a. Dividing the training data into two, namely data before and during the intervention.
   b. Creating a SARIMA model for data before the intervention.
   c. Perform forecasting for data during the intervention using the SARIMA model that has been created.
   d. Make a graph of the residuals of the SARIMA model of the data before the intervention.
   e. Identifying intervention responses, i.e. order b, r, s based on the analysis of the inclusion graph.
   f. Estimating and checking the significance of the parameter estimates of the intervention model.
   g. Performing model diagnostic checks, i.e. freedom test, normality of residual.
   h. Performing overfitting by trying some other orders b, s, r to get the best model order.
   i. Selecting the best intervention model from several candidate models that have been formed based on the MAPE value. The best intervention model is the one with the lowest MAPE value.

5. LSTM Modelling
   a. Divide the training data into two, namely training data and test data.
   b. Creating datasets with predefined time series sequences.
   c. Separating features and targets in each training data and test data.
   d. Reshaping the data to fit the LSTM analysis format.

e. Creating an LSTM model by comparing the number of epochs to be tested, namely 10, 20, 30, 40, 50.
f. Identifying the best LSTM model.

6. Use SARIMA intervention and optimal intervention to predict and test the data and calculate the MAPE value of the model.
7. Comparison of SARIMA model prediction and intervention results Model based on MAPE value. The best model of the two is the Model with the lowest MAPE value.

FINDINGS AND DISCUSSION

Data splitting

The data for the period January 2009 to October 2022 as training data is 166 data, while the data for the period November 2022 to September 2023 as test data is 11 data. The intervention in this study is COVID-19 pandemic in Indonesia. The pandemic has occurred since March 2020, which can be seen as changes in the pattern of time series data, namely the sharp decline in the number of Bali tourists. Therefore, the data is divided into data before the intervention starting from January 2009 to January 2020 (n = 133) and after the intervention starting from February 2020 to October 2022 (n = 21). The data before the intervention will be used for the SARIMA model before the intervention.

SARIMA Data Before Intervention

The data before the intervention shows that the data is not stationary in the average, it can be seen in the ACF plot that forms tails off slowly and is not stationary in the variance which can be seen from the Box-Cox plot that the observation interval does not contain the number 1 with the optimum lambda of 0.

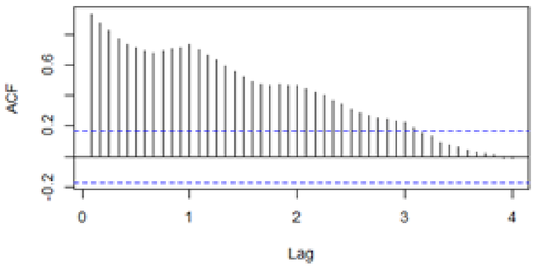


Figure 1. ACF plot of data before intervention that is not yet stationary in the mean.

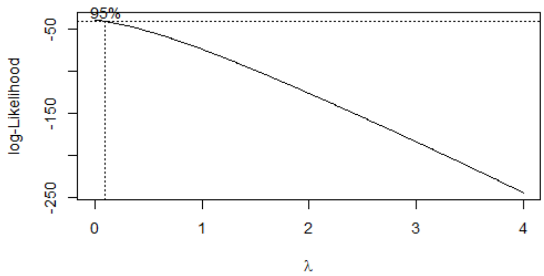


Figure 2. Box-Cox plot of data before intervention that is not yet stationary in variance.

These data are not yet stationary in variety so it is necessary to perform a logarithmic transformation, the resulting lambda of 0 shows that the data is stationary in variance. After that, the first differencing is carried out on the seasonal and non-seasonal so that the data is stationary in the average which can be seen in Figure 3.

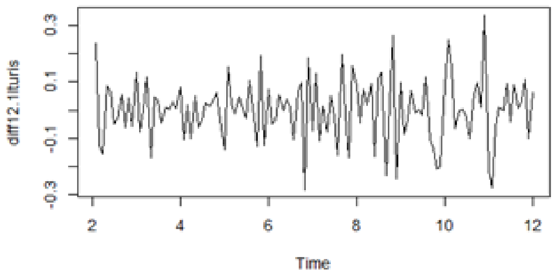
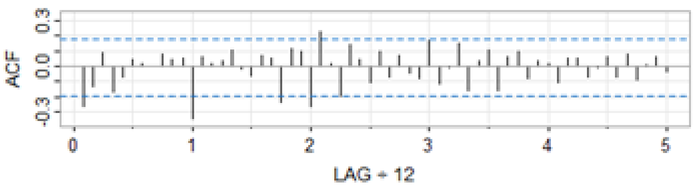


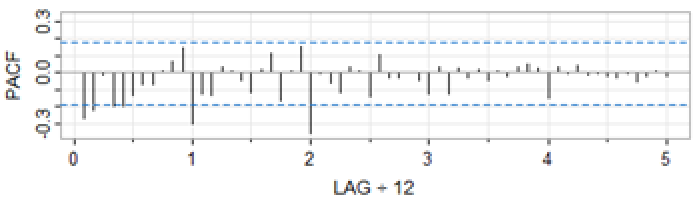
Figure 3. Plot after logarithm transformation and differencing .

Identification of ARIMA(p,d,q)(P,D,Q)s model

The pre-intervention identification of the SARIMA model can be seen in the ACF and PACF diagrams in Figure 4.



(a)



(b)

Figure 4. ACF plot (a) and PACF plot (b) of data before intervention.

Tentative models formed based on ACF and PACF plots and their combinations and crosses are SARIMA (0,1,1)(0,1,2)^{12}, SARIMA (2,1,0)(2,1,0)^{12}, SARIMA (0,1,1)(2,1,0)^{12}, SARIMA (2,1,1)(0,1,2)^{12}, SARIMA (2,1,0)(0,1,2)^{12}, SARIMA (0,1,1)(2,1,2)^{12}, SARIMA (2,1,0)(2,1,2)^{12}, SARIMA (0,1,2)(2,1,0)^{12}, SARIMA (1,1,2)(2,1,0)^{12}. After modeling, there are several SARIMA models whose parameters are significant in Table 3.

Table 2. Estimated values of SARIMA tentative model parameters on data before intervention

Model	Type	Coefficient	P-value	AIC	BIC
SARIMA(0,1,1)(2,1,0)^{12}	MA(1)*	-0.389	0.000	-233.63	-222.48
	SAR(1)*	-0.568	0.000		
	SAR(2)*	-0.459	0.000		
SARIMA(0,1,2)(2,1,0)^{12}	MA(1)*	-0.422	0.000	-237.08	-223.14
	MA(2)*	-0.315	0.004		
	SAR(1)*	-0.536	0.000		
	SAR(2)*	-0.451	0.000		

*parameters that are significant at the 5% real level

Based on Table 2, it can be seen that the best model is the model with significant parameters and the smallest AIC value is SARIMA(0,1,2)(2,1,0)^{12}.

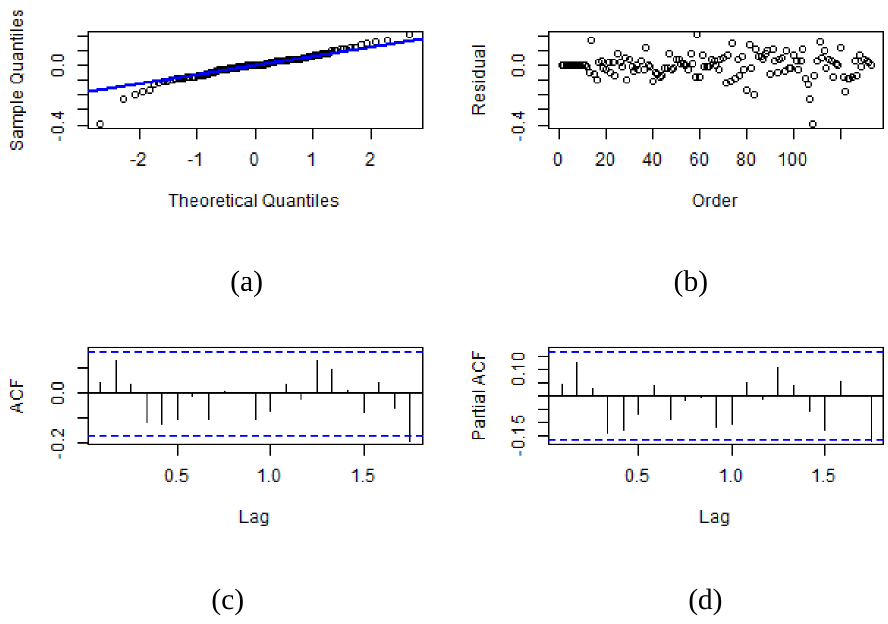


Figure 5. (a) Q-Q plot, (b) Residual vs Order plot, (c) ACF Plot and (d) PACF Plot.

Model diagnostics are carried out to check whether the model built is correct by checking the assumptions on the resulting model residuals. The exploratory results in Figure 5 (a) show that the residuals do not spread normally as the points tend not to follow the 45° line. Most of the points on the plot of the time-ordered residuals move around the zero point as well as the width of the residual band tends to be the same (Figure 5 (b)). This indicates that the variance is homogeneous. Examination of the freedom of the samples based on the exploration results is is presented in Figure 5 (c) and 5 (d). The ACF and PACF plots of the model residuals show that they are independent of each other.

Table 3. Formal test results ARIMA(0,1,2)(2,1,0)^{12}

Assumption Test	P-value	Description
Normality	0.000	The remainder does not spread normally
Freedom of error	0.617	Mutually independent remainders
Homogeneity of residuals	0.696	Homogeneous variance of variance
The mean of the intercepts is equal to zero	0.964	The center value of the bias is zero

The formal tests performed on the model showed that the assumptions were met (p-value > α) i.e. accept H0 at 95% confidence level. Overfitting was performed to compare with the SARIMA model before intervention. ARIMA(0,1,3)(2,1,0)^{12} is the overfitting model performed. The model obtained an AIC of -237.52 and the parameters obtained were insignificant. This proves that the ARIMA(0,1,2)(2,1,0)^{12} model remains the best SARIMA model before the intervention.

Identify Intervention Response

The forecasting results in the model before the intervention, namely ARIMA(0,1,2)(2,1,0)^{12} when the intervention occurs are very different from the actual data. This happens due to the intervention, namely the COVID-19 event. Intervention identification needs to be done by observing the graph of the ARIMA(0,1,2)(2,1,0)^{12} model's residuals.

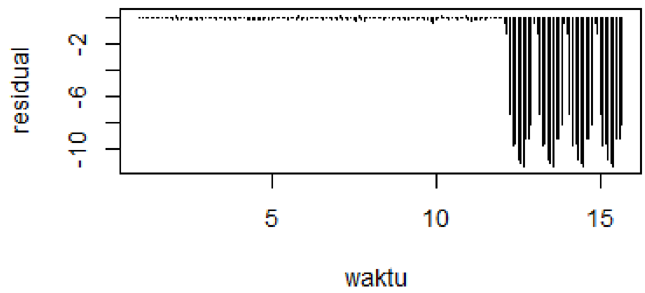


Figure 6. Graph of Model Residuals ARIMA(0,1,2)(2,1,0)^{12}

The graph above shows that the data on the number of Bali tourists immediately dropped dramatically so that the selected order b is 0. Next, the order s is selected by seeing how long the decrease in the number of tourists before returning to normal. The estimated order s is 21 so that 21 trials are tried, then the selection of order r is 1 because the data after the intervention forms a new pattern. The results of estimating some of the best intervention model parameters are shown in Table 5.

Table 4. Parameter estimation values of the best Intervention model

Model	**Type**	**coeffisient**	**P-value**	**AIC**	**BIC**
SARIMA$(0,1,2)(2,1,0)^{12}$. b = 0, s = 3, r = 1	MA(2)	0.080	0.527	3804.9	3820.4
	SAR(2)*	0..074	0.000		
	ω_0*	25995.4	0.000		
	ω_3*	41309.8	0.000		
	δ_1*	0.108	0.000		

*parameters that are significant at the 5% real level

The intervention model with the most significant parameters is intervention models with order b = 0, s = 3, and r = 1. Next, the model diagnostic test will be conducted. The Ljung-Box model results are shown in Table 5. Table 6 shows that the ARIMA $(0,1,2)(2,1,0)^{12}$. b = 0, s = 3, r = 1 model does not have autocorrelation on the side. The residuals of the model are also normally distributed based on the distribution plot of the residuals in appendix 2. The formal test with Kolmogrov-Smirnov also shows that the residuals spread normally because p-value greater than 5% level, namely 0.107.

Table 5. Ljung-Box test results on the intervention model's residuals

Model	**Lag**	**P-value**
ARIMA$(0,1,2)(2,1,0)^{12}$. b = 0, s = 3, r = 1	6	0.0128
	12	0.104
	18	0.2779
	24	0.1203
	30	0.1356

Long Short-Term Memory (LSTM)

LSTM model is one method that can be is one method that can be handle time series data very well. In the initial stage of LSTM model building, the data needs to be organized into sequences, then divided into features and targets to train the model in order to get the best model. After that, reshaping the data into a three-dimensional format is done so that LSTM analysis can be performed. The LSTM model is built by determining the right configuration for the target. In determining the best LSTM model, the parameter chosen to determine the model is epoch by comparing its AIC value. The tested epochs are 10, 20, 30, 40, 50. Based on the smallest AIC, the best LSTM model chosen is the model with epoch 50 which can be viewed in Table 6.

Table 6. Selection of the best epoch value

Model	**Epoch**	**AIC**
1	10	-7.281
2	20	-42.616
3	30	-46.814
4	40	-46.906
5	50	-46.954

Forecasting

The final results of the formation of the intervention SARIMA model, and LSTM on the number of data Bali tourists obtained the best model is ARIMA $(0,1,2)(2,1,0)^{12}$, b = 0, s = 3, r = 1 and LSTM (epoch = 50). Furthermore, in the three models, a comparison of forecasting results is carried out with the parameter that becomes the reference for comparison is MAPE in Table 1. The results of the forecasting comparison can be seen in Table 7 below.

Table 7. Comparison of forecasting results

Period	Forecasting		Actual
	Intervention Model	LSTM Model	
November 2022	289937	285108	287398
December 2022	284935	300052	377276
January 2023	282050	300358	331912
February 2023	280104	330406	323623
March 2023	279322	361262	370695
April 2023	283858	332801	411510
May 2023	301072	349330	439475
June 2023	324007	394855	478198
July 2023	350634	425472	541353
August 2023	376888	454023	522141
September 2023	389051	497090	508350
MAPE	18.67%	11.74%	

Based on this comparison, the better model is the LSTM model because it produces a smaller MAPE of 11.74%. The data plot of the forecasting results is in accordance with the MAPE obtained where the LSTM result data plot is almost in accordance with the actual data plot while the SARIMA Intervention result data plot is less in accordance with the actual data plot. After using forecasting for the next 20 periods using the LSTM model, number of foreign tourists to Bali tends to decrease in October 2023-April 2024 and rises again in May 2024-September 2024 and decreases again in October 2024-May 2025 can be seen in Figure 8.

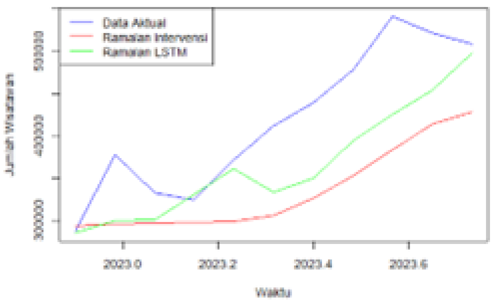


Figure 7. Comparison of actual data plot with forecast.

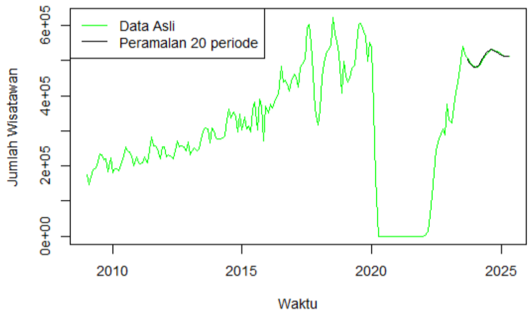


Figure 8. A 20-period forward forecast plot.

CONCLUSION

Forecasting data on number of foreign tourist to Bali can be modeled by SARIMA intervention and LSTM methods. SARIMA $(0,1,2)(2,1,0)^{12}$. b = 0, s = 3, r = 1 is the best intervention model, and LSTM (epoch = 50) is the best LSTM model. The LSTM model is better to use than the intervention SARIMA model because it has a smaller MAPE value to forecast the number of foreign tourist to Bali. Forecasting using LSTM for the next 20 periods shows that the number of foreign tourist to Bali tends to decrease from October 2023 to April 2024 and increases again from May 2024 to September 2024, and decreases again from October 2024 to May 2025.

Forecasting using LSTM is considered to describe the number of foreign tourist to Bali in the next period. However, the forecasting results need to be checked again because the resulting MAPE is not below 10%. The author suggests using other more accurate methods to get a smaller MAPE. In addition, the author also suggests adding more data to get more accurate forecasting results. Based on the forecasting that has been done for the next 20 months, the government can anticipate the prediction of declining tourist visits in the period October 2023 to April 2024 and October 2024 to May 2025 by bringing an innovation to Bali tourism, such as holding new traditional festivals, creating new tourist attractions, forming creative tourism, or other innovative ideas that can be implemented to increase Bali tourist visits.

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