Forecasting The Number of Foreign Tourism Visits to Indonesia using Seasonal Autoregressive Integrated Moving Average (SARIMA) and Holt-Winters Approach

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Abstract. The tourism sector is one of the economic sectors that shows the fastest growth rate and is the largest foreign exchange contributor in a large number of countries, including Indonesia. In the third quarter of 2023, Indonesia's tourism sector generated more than USD 6 billion, which is equivalent to 3.76% of Indonesia's GDP. Foreign tourists have high potential in supporting tourism stability and economic growth. With the target of foreign tourist visits for 2023 reaching 7.4 million, it is important to forecast the number of foreign tourism visits accurately. This study aims to analyze the prediction results of forecasting the number of foreign tourist visits to Indonesia for the period from January 2023 to December 2023. The data used is data on the number of foreign tourist visits to Indonesia for the period from January 2013 to December 2023. The methods used in this study are the Seasonal Autoregressive Integrated Moving Average (SARIMA) and Holt-Winters methods. The models generated in this study are SARIMA$(1,1,0)(0,1,1)^{12}$ and Holt-Winters with parameters alpha 0.6, beta 0.1, and gamma 0.1. Based on the comparison of accuracy values, it is known that the SARIMA model has a better accuracy value than the Holt-Winters model. This is because the RMSE and AIC values of the SARIMA model are smaller than the Holt-Winters model, which are 113,504.54 and 313.17. Therefore, based on this research, the SARIMA method is a suitable method for forecasting the number of foreign tourist visits for the period January 2023 to December 2023.

Keywords: Forecasting, Foreign Tourists, Economy, SARIMA, Holt-Winters.

1 Introduction

The tourism sector is one of the economic sectors that shows the fastest growth rate and is the largest contributor to foreign exchange in many countries, including Indonesia [1]. Based on the World Travel and Tourism Council report (2023), the travel and tourism sector contributed 7.6% to global economic growth through Gross Domestic Product (GDP). In the third quarter of 2023, Indonesia's tourism sector generated more

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USD 6 billion, which is equivalent to 3.76% of Indonesia's GDP [2].

Indonesia's natural wealth and cultural heritage have the potential to attract foreign tourists. Data from the Ministry of Tourism and Creative Economy show that the number of foreign tourist visits to Indonesia reached a high of 16.1 million in 2019. However, in 2020 there was a very drastic decline in the number of foreign tourist visits to Indonesia due to the COVID-19 pandemic with the number of foreign tourism visits only reaching 4 million. This created new challenges for the tourism sector. After the decline, the transition from the pandemic phase to the endemic phase became a momentum for the recovery of national tourism to rise to be stronger [3].

By the end of 2022, the number of foreign tourist arrivals had reached 3.92 million, exceeding the target of 3.6 million visitors [4]. Therefore, foreign tourists have a significant role in the Indonesian economy, not only contributing to increasing foreign exchange but also triggering the growth of supporting sectors such as transportation, accommodation, and culinary. The high financial potential of foreign tourists, the development of the tourism sector is crucial in reviving the stability of the tourism sector, and making a positive contribution to national economic growth [5]. Given the ambitious target for 2023 of 7.4 million foreign tourist arrivals, research on forecasting the number of foreign tourist arrivals is very important.

Forecasting is a method used to estimate events that will occur in the future based on past data [6]. Forecasting usually uses time series data to find patterns of past events that can be used to predict patterns of future events. In the context of time series data forecasting, seasonal data patterns are often found. Seasonality can be defined as the tendency of data patterns to repeat in each specific period. Data related to the number of foreign tourist arrivals often has a consistent seasonal pattern, unless there are unexpected events in a certain period. Popular methods used for data analysis with seasonal patterns are the Seasonal Autoregressive Integrated Moving Average (SARIMA) and Holt-Winters methods.

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model is a development of the Autoregressive Integrated Moving Average (ARIMA) model which has a seasonal pattern [7]. The SARIMA method is used to forecast non-stationary time series, such as tourism demand data which tends to fluctuate and has a seasonal pattern [8]. In addition to the SARIMA method, the Holt-Winters method is also highlighted in this study. This method is particularly effective for modeling data with seasonal patterns. By introducing level, trend, and seasonal components, Holt-Winters can provide a better understanding of the recurring changes in tourism demand.

Based on the background that has been described, researchers are interested in conducting research on forecasting the number of foreign tourist visits to Indonesia using the SARIMA and Holt-Winters approaches using data published by the Ministry of Tourism and Creative Economy regarding Statistics on Foreign Tourist Visits for the period from January 2013 to December 2023. This study aims to analyze the comparison of the prediction results of the SARIMA and Holt-Winters methods to obtain a prediction model for the number of foreign tourist visits to Indonesia, and determine the accuracy value of the two methods.

2 Fundamental Theory

2.1 Seasonal Autoregressive Integrated Moving Average (SARIMA)

Seasonal Autoregressive Integrated Moving Average (SARIMA) is a development of the Autoregressive Integrated Moving Average (ARIMA) model that has a seasonal pattern. This method is used to forecast non-stationary time series, such as tourism demand data that tends to fluctuate [8].

$$\mathrm{SARIMA}(p,d,q)(P,D,Q)^{s} \tag{1}$$

Equation (1) explains that (p,d,q) is the order of AR, differencing, and MA for the non-seasonal model. Meanwhile, (P,D,Q) is the order of AR, differencing, and MA for the seasonal model. As well as the symbol s which means the number of periods per season. The multiplicative SARIMA model formula is shown in equation (2).

$$\phi_p(B)\Phi_P(B^{\,s})(1 - B)^d\,(1 - B^{\,s})^D X_t = \theta_q(B)\Theta_Q(B^{\,s})\varepsilon_t \tag{2}$$

2.2 Stationarity Test

Stationarity test is a test conducted to see whether the data is stationary or not. Time series data can be said to be stationary if there is no tendency for changes in variance and average. Box-Cox transformation is a method used to overcome problems if nonstationary data is found or stabilize the variance in the data [9]. Data can be said to be stationary in variance, if the value of λ = 1.

$$T\left(X_t^{(\lambda)}\right) = \frac{X_t^{(\lambda)}-1}{\lambda}\ , -1 < \lambda < 1 \tag{3}$$

Where $T\left(X_t^{(\lambda)}\right)$ is the transformed value, X_t is the time series data at period t, and λ is the transformation parameter (-1< λ < 1). Augmented Dickey Fuller (ADF) is a method used to test data stationarity in mean [10]. The ADF statistical test hypothesis is as follows [11].
H_0: data doesn't meet the assumption of stationary in the mean

H_1: data meet the assumption of stationary in the mean

$$\Delta X_t = \phi X_{t-1} + \varepsilon_t \tag{4}$$

Where ΔX_t is the difference between the data value t and the $t-1$ data, ϕ is the estimated Autoregressive (AR) parameter, and ε_t is the time series residual in period t.

2.3 Normality Test

The normality test is a method used to determine whether the data distribution is normally distributed or not. Normality tests can be carried out using the Kolmogorov-Smirnov, Shapiro-Wilk methods, and can be seen from graph visualization [12]. The Kolmogorov-Smirnov test statistic is defined by equation (5).

$$D = max\left(\frac{t}{n} - F(X_t), F(X_t) - \frac{t-1}{n}\right), t = 1, 2, \dots, n \tag{5}$$

Where n is the number of data, $F(X_t)$ is the normal distribution cumulative function, and t is the observation index ($t = 1, 2, \dots, n$).

2.4 White Noise Test

The white noise test is conducted to determine whether there is autocorrelation in the residual model [13]. This test can be done using the Ljung-Box test. The test is carried out with the following hypothesis.

$H_0: \rho_1 = \rho_2 = \dots = \rho_h = 0$

H_1: at least one $\rho_k \neq 0, k = 1, 2, \dots, h$

$$Q = n(n+2)\sum_{k=1}^{h} \frac{\rho_k^2}{n-k} \tag{6}$$

Where n is the number of data, ρ_k is the autocorrelation at the k lag, and k is the k time lag with $k = 1,2,\dots,h$.

2.5 Holt-Winters

The Holt-Winters method is a forecasting technique used to forecast time series data that has a seasonal pattern. Holt-Winters is suitable for use when time series data has seasonal fluctuations and trend changes. This method can handle level, seasonal, and trend factors simultaneously in time series data [14]. Formula of the initial estimated values of level (L_t), trend (b_t), and seasonality (S_{t-s}).

$$L_0 = \left(\frac{X_1 + X_2 + X_3 + \dots + X_s}{s}\right) \tag{7}$$

$$b_0 = \frac{1}{s}\left(\frac{X_{s+1} - X_1}{s} + \dots + \frac{X_{s+s} - X_s}{s}\right) \tag{8}$$

$$S_{t-s} = \frac{X_t}{L_0} \tag{9}$$

Formula of the smoothing level (L_t), trend (b_t), and seasonality (S_t) values.

$$L_t = \alpha\left(\frac{X_t}{S_{t-s}}\right)(1-\alpha)(L_{t-1} + b_{t-1}) \tag{10}$$

$$b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1} \tag{11}$$

$$S_t = \gamma\left(\frac{X_t}{L_t}\right) + (1-\gamma)S_{t-s} \tag{12}$$

The Multiplicative Holt-Winters forecasting model is formulated in equation (13).

$$F_{t+m} = (L_t + b_t m)S_{t-s+m} \tag{13}$$

where,

F_{t+m} : forecasting result at the time period $t+m$
L_t : smoothing level value in the period t
b_t : smoothing trend value in the period t
S_{t-s+m} : seasonal smoothing value $t-s+m$
s : number of periods per season
m : forecasting time length

2.6 Root Mean Squared Error (RMSE)

Root Mean Squared Error (RMSE) is one of the methods for evaluating the accuracy of a model. This is done to measure the extent of the difference between the value predicted by a model and the actual value. RMSE is often used in cases when the data being analyzed has outlier values. Accuracy will be higher if the RMSE value is smaller. The RMSE formula is shown in equation (14).

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(X_t - \hat{X}_t)^2} \quad (14)$$

Where X_t is the time series data at period t, $\hat{X}_t$ is the forecasted value at time t, and n is the number of testing data.

2.7 Akaike Information Criterion (AIC)

Akaike Information Criterion (AIC) is one of the methods used to measure how the model can describe data with good parameters in estimating data [15]. The AIC value is used to select the best SARIMA model chosen. Where, the best model is obtained in the model that has the lowest AIC value. The general form of AIC is equation (15).

$$AIC = n\, ln \sum_{t=1}^{n} \varepsilon_t^2 + 2j \quad (15)$$

Where n is the number of data, ε_t is the residual, and j is the number of estimated parameters.

3 Methodology

3.1 Data Collection

The data used in this study are secondary data on the number of foreign tourist visits from January 2013 to December 2023. The data collected comes from the publication of the Indonesian Ministry of Tourism and Creative Economy on the official website kemenkraf.go.id.

3.2 Data Preprocessing

Secondary data that has been collected is subjected to data preprocessing. This step is done by creating a boxplot to check whether there is missing data or not. After that, data exploration and visualization are carried out to obtain certain information such as mean value, standard deviation, minimum value, and maximum value.

3.3 Split Data

The data is divided into two, namely training data and testing data. Data on foreign tourist visits from January 2013 to December 2022 is used as training data, while data from January 2023 to December 2023 is used as testing data. This shows that the data used for training is 120 data and testing data is 12 data.

3.4 Modeling Training Data with SARIMA Method

The steps of the Seasonal Autoregressive Integrated Moving Average (SARIMA) method are as follows.

1) Stationarity tests on data can be identified through analysis of time series data plots, namely Autocorrelation Function (ACF) plots and Partial Autocorrelation Function (PACF) plots. Stationarity tests can also be performed using Box-Cox and Augmented Dickey Fuller (ADF) plots. The first step is to test stationarity in variance using the Box-Cox plot. Data is said to be stationary in variance if the lambda (λ) value is equal to one and for data that is not stationary in variance, Box-Cox transformation can be performed. The next step is to test stationarity in the average using the ADF test. Data is said to be stationary in the average if the p-value is smaller than alpha and for data that is not stationary in the average, differencing transformation can be performed.
2) Identify the model order (p, d, q) for non-seasonal models and (P, D, Q, s) for seasonal models. Identification is done by looking at the lag intersection on the ACF plot, where the plot is used to identify the Moving Average (MA) and Seasonal Moving Average (SMA) models, while the PACF plot is used to identify the Autoregressive (AR) and Seasonal Autoregressive (SAR) models. This order identification will be done several times until the order for the non-seasonal model and seasonal model is obtained.
3) Based on the identification carried out, several SARIMA models can be determined to find the appropriate model parameter coefficients.
4) Estimation and testing of parameters.
5) The assumption test uses normality test and white noise test.
6) Selecting the best SARIMA model based on the smallest RMSE and AIC values.
7) Forecasting using the best SARIMA model that has been obtained in the previous step.

3.5 Modeling Training Data with Holt-Winters Method

The steps in analyzing with the Holt-Winters method are as follows.

1) Determine the seasonal length according to the seasonal length in the SARIMA method.
2) Determine the values of the parameters α, β, and γ. The parameters α, β, and γ are in the interval $0 < \alpha, \beta, \gamma < 1$. The optimal parameters chosen are those that are able

to minimize the error value. In determining these parameters, it is done with the help of RStudio.

3) Calculate the initial estimated values of level (L_t), trend (b_t), and seasonality (S_{t-s}).
4) Calculate the smoothing level (L_t), trend (b_t), and seasonality (S_t) values.
5) Forecasting using the best parameters that have been obtained in the previous step.

3.6 Evaluation of Model Accuracy

Evaluate the accuracy of SARIMA and Holt-Winters models using Akaike Information Criterion (AIC) and Root Mean Squared Error (RMSE).

3.7 Comparison of Forecasting Results with Testing Data

Comparing the value of the SARIMA and Holt-Winters method forecasting results with the testing data. The comparison is done to determine the forecasting results of the two methods.

3.8 Conclusion of Analysis Results

Based on the analysis carried out, some information is obtained to answer the problem formulation. The information obtained from the results of the forecasting analysis using the SARIMA and Holt-Winters methods is summarized.

4 Result and Discussion

4.1 Exploratory Data Analysis

The data used in this study is secondary data on the number of foreign tourist visits from January 2013 to December 2023. Fig. 1 shows that in the period January 2013 to December 2023, foreign tourist visits to Indonesia show fluctuations that occur due to various factors such as summer vacation, new year vacation, year-end vacation, and others. Based on publications from BPS (2021), in 2020 the number of foreign tourist visits to Indonesia experienced a significant decline due to the COVID-19 pandemic, with total visits reaching only 4.05 million, a decrease of almost 75% compared to 2019 which reached 16.11 million visits. Peak visitation occurred in January with 1.29 million visits, prior to the introduction of crossing restrictions. The pattern of visits changed significantly, with the highest decline recorded in August at 89.44%, followed by declines in July and September at 89.39% and 89.27% respectively. In contrast, the lowest decline occurred in February at 29.84%. In addition to the change in visitation pattern, the monthly growth pattern also experienced a drastic change, where the increase only occurred in January by 7.38%, while the following months showed a sharp decline due to the impact of the pandemic and travel restriction policy. Based on publications from BPS (2022), in the years before the pandemic, the peak of foreign tourist visits usually occurred in the middle of the year, around July to August. However, in 2021, the pattern of foreign tourist visits is almost evenly distributed in every month. From January to September, the pattern of foreign tourist visits is relatively stable, with the number of visits ranging from 100 thousand to 140 thousand visits per month.

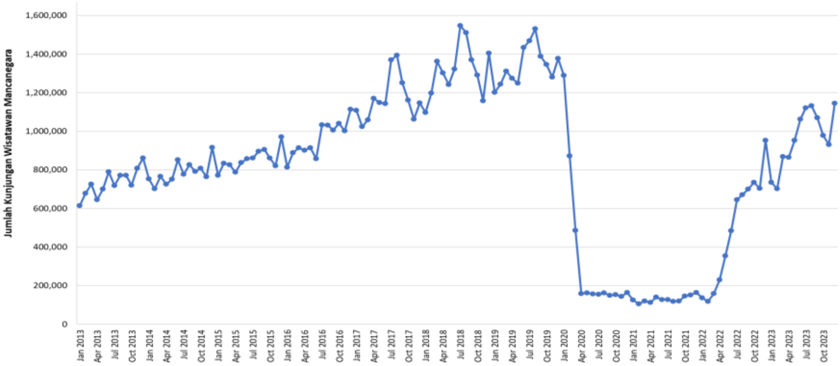


Fig. 1. Time Series Plot of Number of Foreign Tourist Visits to Indonesia from January 2013 - December 2023.

4.2 SARIMA Method

Data on the number of foreign visits to Indonesia that have been obtained are analyzed using the Seasonal Autoregressive Integrated Moving Average (SARIMA) method with the help of Minitab 18.

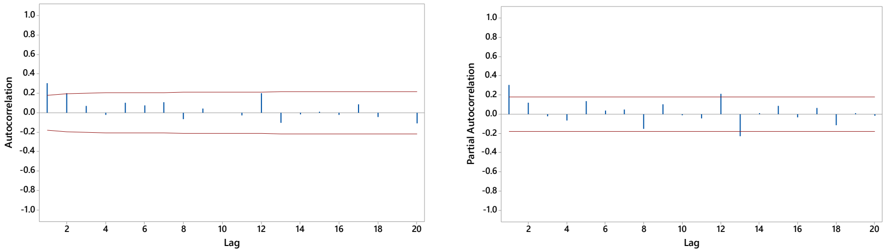
Stationary Test

The first step in performing SARIMA analysis is to test stationarity in variance in the training data. This test is carried out using a Box-Cox plot to check whether the data is stationary in variance or not. Data can be said to be stationary in variance, if the value of $\lambda = 1$. In the first transformation, the rounded value or lambda (λ) is 0.50. This shows that the data on the number of foreign tourist arrivals to Indonesia in the period January 2013 to December 2022 is not stationary in variance, so it is necessary to do the Box-Cox transformation for the second time. The results of the second Box-Cox transformation show that the lambda (λ) value obtained is 1. This indicates that the data on the number of foreign tourist arrivals to Indonesia in the period January 2013 to December 2022 have met the stationarity test in variance with the transformation $X_t = \sqrt[4]{X_t}$.

The next step is the stationarity test in the mean. This test is carried out using the Augmented Dickey-Fuller (ADF) test to check whether the data is stationary in the mean or not. In testing using the ADF test, data can be said to be stationary in the mean if the p-value < alpha (0.05). The results of the ADF test conducted on the transformed data show that the p-value of 0.6724 > alpha (0.05). This results in a decision to fail to reject H_0, which means that the data does not meet the assumption of stationarity in the mean. The results of differencing using the ADF test show that the p-value is 0.0334 < alpha (0.05). This results in a decision to reject H_0, which means that the data meets the assumption of stationarity in the mean, so the analysis can proceed to the next stage.

Identification of SARIMA Model

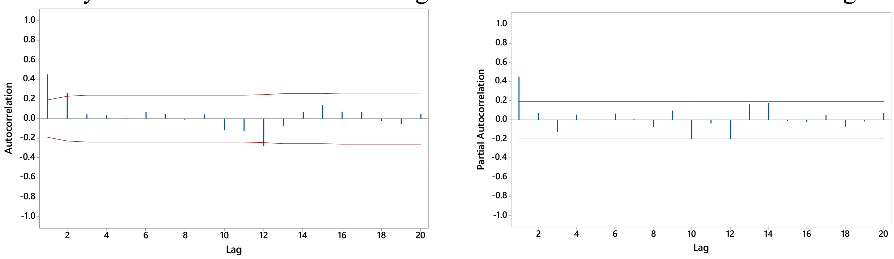
Identify the model order (p, d, q) for non-seasonal models and (P, D, Q, s) for seasonal models. Identification is done by looking at the lag intersection on the ACF plot, where the plot is used to identify the Moving Average (MA) and Seasonal Moving Average (SMA) models, while the PACF plot is used to identify the Autoregressive (AR) and Seasonal Autoregressive (SAR) models.



(a) (b)

Fig. 2. (a) ACF Plot of One-Time Non-Seasonal Differencing Data (lag = 1) and (b) PACF Plot of One-Time Non-Seasonal Differencing Data (lag = 1).

Based on Fig. 2, the ACF plot shows that the data intersects the interval line at lag 1 while the PACF plot for the non-seasonal differencing data shows that the data intersects the interval line at lag 1, lag 12, and lag 13. Therefore, the order for the non-seasonal model is p = 1, d = 1, q = 1. However, on the PACF plot it is known that the data also intersects at lag 12 which means that the data has a seasonal model so it is necessary to do differencing to identify the seasonal order. Differencing to find the seasonal order is done with lag = 12.



(a) (b)

Fig. 3. (a) ACF Plot of One-Time Seasonal Differencing Data (lag = 12) and (b) PACF Plot of One-Time Seasonal Differencing Data (lag = 12).

Based on Fig. 3, the ACF plot for seasonal differencing data shows that the data cuts the interval line at lag 1, lag 2, and lag 12. In addition, the PACF plot for seasonal differencing data shows that the data cuts the interval line at lag 1. Therefore, the order for the non-seasonal model is P = 1 and D, d = 1, Q = 1 with s = 12.

Significance of Model Parameters

Testing the significance of the SARIMA model parameters is carried out to determine whether the model is feasible to use or not. The model can be said to be significant if the p-value < alpha (0.05).

Table 1. Significance Testing of SARIMA Model Parameters.

Model	Parameter	Estimasi	p-value
SARIMA(0,1,1)(0,1,1)^{12}	MA (1)	-0.2277	0.021
	SMA (1)	0.9106	0.000
SARIMA(1,1,0)(1,1,0)^{12}	AR (1)	0.2991	0.002
	SAR (1)	-0.3268	0.001
SARIMA(1,1,0)(0,1,1)^{12}	AR (1)	0.2592	0.007
	SMA (1)	0.9057	0.000
SARIMA(0,1,1)(1,1,0)^{12}	MA (1)	-0.3317	0.001
	SAR (1)	-0.2367	0.016
SARIMA(0,1,1)(0,1,2)^{12}	MA (1)	-0.2397	0.015
	SMA (1)	0.667	0.000
	SMA (2)	0.127	0.229
SARIMA(1,1,0)(0,1,2)^{12}	AR (1)	0.2910	0.003
	SMA (1)	0.651	0.000
	SMA (2)	0.105	0.174
SARIMA(1,1,1)(1,1,0)^{12}	AR (1)	0.638	0.006
	MA (1)	0.377	0.165
	SAR (1)	-0.3279	0.001
SARIMA(1,1,1)(0,1,1)^{12}	AR (1)	0.626	0.017
	MA (1)	0.402	0.188
	SMA (1)	0.9050	0.000
SARIMA(1,1,0)(1,1,1)^{12}	AR (1)	0.2648	0.007
	SAR (1)	0.080	0.501
	SMA (1)	0.9119	0.000
SARIMA(0,1,1)(1,1,1)^{12}	MA (1)	-0.2282	0.021
	SAR (1)	0.073	0.542
	SMA (1)	0.9142	0.000
SARIMA(1,1,1)(0,1,2)^{12}	AR (1)	0.599	0.018
	MA (1)	0.341	0.245
	SMA (1)	0.643	0.000
	SMA (2)	0.150	0.158
SARIMA(1,1,0)(1,1,2)^{12}	AR (1)	0.2754	0.005
	SAR (1)	-0.556	0.290
	SMA (1)	0.133	0.792
	SMA (2)	0.614	0.111
SARIMA(0,1,1)(1,1,2)^{12}	MA (1)	-0.2266	0.023
	SAR (1)	-0.564	0.317

	SMA (1)	0.136	0.802
	SMA (2)	0.614	0.141
SARIMA(1,1,1)(1,1,1)^{12}	AR (1)	0.604	0.024
	MA (1)	0.308	0.231
	SAR (1)	0.078	0.515
	SMA (1)	0.9071	0.000
SARIMA(1,1,1)(1,1,2)^{12}	AR (1)	0.629	0.012
	MA (1)	0.386	0.187
	SAR (1)	-0.560	0.254
	SMA (1)	0.120	0.798
	SMA (2)	0.628	0.082

Table 1 shows that there are four significant models, because they have a p value < alpha (0.05). The four significant models are SARIMA(0,1,1)(0,1,1)^{12}, SARIMA(1,1,0)(1,1,0)^{12}, SARIMA(1,1,0)(0,1,1)^{12}, and SARIMA(0,1,1)(1,1,0)^{12}.

Assumption Test

The assumption tests carried out are normality test and white noise test. Normality test is a method used to determine whether the data distribution is normally distributed or not. The normality test in this study used the Kolmogorov-Smirnov method.

Table 2. Normality Test of SARIMA Model.

Model	Uji Normalitas	
	p-value	Keterangan
SARIMA(0,1,1)(0,1,1)^{12}	> 0.150	Memenuhi
SARIMA(1,1,0)(1,1,0)^{12}	< 0.010	Tidak Memenuhi
SARIMA(1,1,0)(0,1,1)^{12}	0.116	Memenuhi
SARIMA(0,1,1)(1,1,0)^{12}	< 0.010	Tidak Memenuhi

To find out whether there is autocorrelation in the residuals, a white noise assumption test is performed using the Ljung-Box test. Residuals are said to fulfill the white noise assumption if the p-value on each lag is greater than alpha (0.05).

Table 3. White Noise Test of SARIMA Model

Model	p-value Ljung-Box			
	Lag 12	Lag 24	Lag 36	Lag 48
SARIMA(0,1,1)(0,1,1)^{12}	0.822	0.393	0.276	0.371
SARIMA(1,1,0)(0,1,1)^{12}	0.928	0.410	0.352	0.400

Table 2 and Table 3 show that the SARIMA$(0,1,1)(0,1,1)^{12}$ and SARIMA$(1,1,0)(0,1,1)^{12}$ models fulfill the normality assumption test and white noise test.

The Best SARIMA Model

To determine the best SARIMA model from the two models can be done by identifying the smallest RMSE and AIC values.

Table 4. RMSE and AIC Results of SARIMA Model

Model	RMSE	AIC
SARIMA$(0,1,1)(0,1,1)^{12}$	121,941.94	314.89
SARIMA$(1,1,0)(0,1,1)^{12}$	113,504.54	313.17

Table 4 shows that the SARIMA model that has the smallest RMSE and AIC values is the SARIMA$(1,1,0)(0,1,1)^{12}$ model of 113,504.54 and 313.17. The SARIMA$(1,1,0)(0,1,1)^{12}$ model equation is as follows.

$$\phi_p(B)\Phi_P(B^{\,s})(1-B)^d\,(1-B^{\,s})^D\,X_t \;=\; \theta_q(B)\Theta_Q(B^{\,s})\varepsilon_t$$

$$X_t = X_{t-1} + X_{t-12} - X_{t-13} + 0.2592X_{t-1} - 0.2592X_{t-2} - 0.2592X_{t-13} + 0.2592X_{t-14} + \varepsilon_t + 0.9057\varepsilon_{t-12}$$

Forecasting with The Best SARIMA Model

In the analysis using the SARIMA method, the best model is SARIMA$(1,1,0)(0,1,1)^{12}$, using the help of Minitab 18, forecasting can be done for the next 16 months starting from January 2023 to December 2023. The comparison results of testing data and forecasting results are shown in Table 5.

Table 5. Forecasting the Best SARIMA Model

Data *Testing* (X_t)	*Forecast* ($\hat{X}_t$)
735,947	916,518
701,931	897,622
869,243	904,117
865,810	866,261
953,713	887,150
1,062,789	929,559
1,121,189	988,291
1,132,638	1,003,537
1,070,245	965,613
978,499	954,837
931,227	924,180
1,144,542	1,024,480

Fig. 4 shows that the forecasting results of the SARIMA$(1,1,0)(0,1,1)^{12}$ model do not have a significant difference with the actual or testing data and have a fairly stable pattern following the testing data pattern. In addition, the fitted value results have a pattern that follows the actual data, where the fitted value comes from the traning data that has been modeled using the best SARIMA model, SARIMA$(1,1,0)(0,1,1)^{12}$.

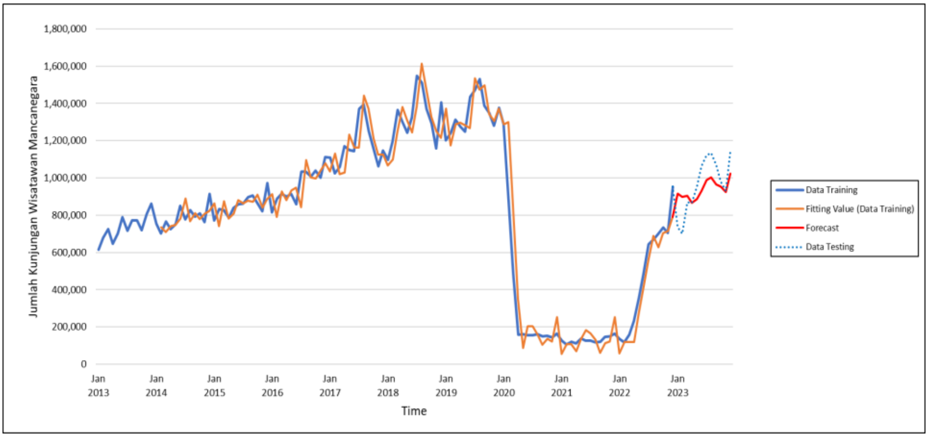


Fig. 4. Time Series Plot of Actual Data with SARIMA Method Forecasting Results.

4.3 Holt-Winters Method

Data on the number of foreign visits to Indonesia that has been obtained is analyzed using the Holt-Winters method in RStudio.

Seasonal Length

The seasonal length to perform the analysis using the Holt-Winters method is determined by the same steps as the SARIMA method, namely by looking at the ACF and PACF plots. Therefore, the seasonal length to be used in this analysis is s = 12.

Alpha, Beta, Gamma Parameters

Determination of the value of alpha (α), beta (β), and gamma (γ) parameters can be done by combining several values in the interval $0 < \alpha, \beta, \gamma < 1$ using RStudio. The parameters combined in this study were 729 combinations. The optimal parameter chosen is the parameter that can minimize the error value. The results of the calculation of α, β, and γ values using RStudio assistance obtained the best parameter combination is alpha of 0.6, beta of 0.1, and gamma of 0.1. The three parameter values will be used in the calculation of the Holt-Winters method for training data.

Initial Estimated Values of Level (L_t), Trend (b_t), and Seasonality (S_{t-s})

The next step is the calculation to determine the initial value of the estimated level (L_t), trend (b_t), and seasonality (S_{t-s}) of the data on the number of foreign tourist visits to Indonesia using Microsoft Excel.

Smoothing Level (L_t), Trend (b_t), and Seasonality (S_t) Values

After obtaining the parameter values α, β, γ and the initial estimated value, the next step is to calculate the smoothing level (L_t), trend (b_t), and seasonality (S_t) values.

Forecasting with Holt-Winters Method

In the analysis using the Holt-Winters method, forecasting can be done for the next 16 months starting from January 2023 to December 2023.

Table 6. Forecasting with Holt-Winters Method

Data *Testing* (X_t)	*Forecast* ($\hat{X}_t$)
735,947	723,160
701,931	762,469
869,243	845,638
865,810	791,067
953,713	890,157
1,062,789	1,034,529
1,121,189	1,061,823
1,132,638	1,142,272
1,070,245	1,166,465
978,499	1,154,665
931,227	1,247,835
1,144,542	1,431,401

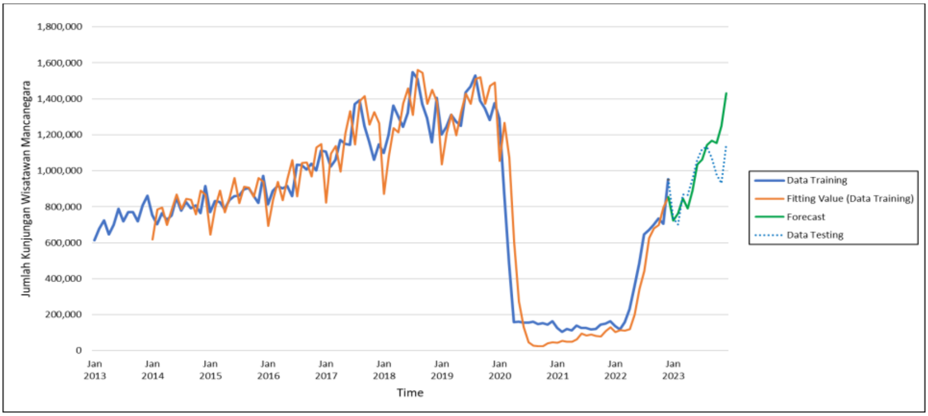


Fig. 5. Time Series Plot of Actual Data with Holt-Winters Method Forecasting Results

Fig. 5 shows that the forecasting results of the Holt-Winters method do not have much difference with the actual data or testing data and have a fluctuating pattern that tends to rise. In addition, the fitted value results have a pattern that follows the actual data, where the fitted value comes from the training data that has been smoothed using the optimum parameters, namely alpha of 0.6, beta of 0.1, and gamma of 0.1. However, when compared to the fitted results of the SARIMA model, it can be seen that the SARIMA model pattern is closer to the actual data pattern and the Holt-Winters model is slightly closer to the actual data pattern.

4.4 Evaluation of Model Accuracy

From the results of forecasting using the SARIMA and Holt-Winters methods, it is possible to evaluate the accuracy of the model to choose the best method for forecasting data on the number of foreign tourist visits to Indonesia for the period from January 2023 to December 2023. Evaluation of model accuracy is seen from the RMSE and AIC values of the two methods.

Table 7. Comparison of Model Accuracy Evaluation Results

Metode	RMSE	AIC
SARIMA	113,504.54	313.17
Holt Winters	141,788.62	320.51

Table 7 shows that the model generated from the analysis using the SARIMA method is 113,504.54 and 313.17, these values are smaller than the RMSE and AIC values generated by the Holt-Winters model which has RMSE and AIC values of 141,788.62 and 320.51. Therefore, the best method used in predicting data on the number of foreign tourist visits to Indonesia for the period from January 2023 to December 2023 is the SARIMA method.

4.5 Comparison of Forecasting Results of SARIMA and Holt-Winters Methods

From the forecasting results using the SARIMA and Holt-Winters methods, visualization is carried out on the two methods to see the comparison of the predicted values.

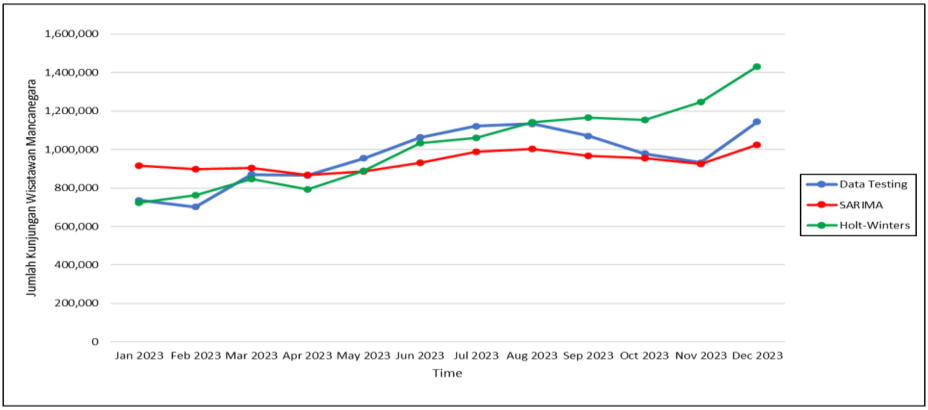


Fig. 6. Comparison of Testing Data with Forecast Results of Both Methods

Fig. 6 shows a comparison of the results of forecasting the number of foreign tourist visits to Indonesia in 2023 based on two analysis methods, namely SARIMA and Holt-Winters. The testing data shows a consistent increase from January 2023 to December 2023, with peak visitation occurring in December 2023 near 1.4 million. SARIMA predictions show high stability following a pattern similar to the actual data, although in certain months there are values that are slightly below the actual data. Meanwhile, Holt-Winters predictions show greater fluctuations with an upward trend. From the overall analysis, it can be concluded that the SARIMA method is more reliable in consistency and closeness to the actual data throughout the period, while Holt-Winters shows larger fluctuations and more positive predictions at the end of the year.

Table 8. Comparison of SARIMA and Holt-Winters Forecasting Results

Data	**Data Testing (X_t)**	**Hasil Forecast SARIMA**	**Hasil Forecast Holt-Winters**
X_{121}	735,947	916,518	723,160
X_{122}	701,931	897,622	762,469
X_{123}	869,243	904,117	845,638
X_{124}	865,810	866,261	791,067
X_{125}	953,713	887,150	890,157
X_{126}	1,062,789	929,559	1,034,529
X_{127}	1,121,189	988,291	1,061,823
X_{128}	1,132,638	1,003,537	1,142,272
X_{129}	1,070,245	965,613	1,166,465
X_{130}	978,499	954,837	1,154,665
X_{131}	931,227	924,180	1,247,835
X_{132}	1,144,542	1,024,480	1,431,401
	RMSE	**113,504.54**	**141,788.62**
	AIC	**313.17**	**320.51**

Table 8 shows that the SARIMA$(1,1,0)(0,1,1)^{12}$ model has smaller RMSE and AIC values compared to the Holt-Winters model with parameters alpha = 0.6, beta = 0.1, and gamma = 0.1. It can be concluded that the SARIMA model has the best accuracy value seen from the RMSE and AIC values of the two models which have a difference of 28,284.09 for RMSE and 7.34 for AIC. The Holt-Winters model has an RMSE value of 141,788.62 and an AIC of 320.51, while the RMSE value of the SARIMA model is 113,504.54 and the AIC is 313.17. Therefore, the best model used in forecasting the number of foreign tourist visits to Indonesia for the period from January 2023 to December 2023 is SARIMA.

5 Conclusion

Based on the results of the analysis and discussion previously discussed, it is concluded that the SARIMA(1,1,0)(0,1,1)^{12} model has better accuracy results than the model with the Holt-Winters method using alpha parameters of 0.6, beta of 0.1, and gamma of 0.1. Where, from the SARIMA(1,1,0)(0,1,1)^{12} model, the accuracy value of RMSE is 113,504.54 and AIC is 313.17. Meanwhile, the Holt-Winters model obtained an RMSE accuracy value of 141,788.62 and an AIC of 320.51. Therefore, the best model used in forecasting the number of foreign tourist visits to Indonesia for the period from January 2023 to December 2023 is SARIMA.

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