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EVALUATING THE PERFORMANCE OF HOLT-WINTERS AND ARIMA FORECASTING MODELS FOR DOMESTIC TOURIST ARRIVALS IN EAST JAVA

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Abstract: This study aims to forecast the number of domestic tourist visits in East Java Province using the Holt-Winters and ARIMA methods. Monthly data from 2021 to 2025 were obtained from the Central Bureau of Statistics (BPS) and analyzed using R. The results show that the data exhibit fluctuations and seasonal patterns. The ARIMA analysis identified ARIMA(1,1,0) as the selected model after first-order differencing. Based on MAE, RMSE, and MAPE, Holt-Winters achieved lower error values than ARIMA(1,1,0). Therefore, Holt-Winters was selected as the forecasting method for domestic tourist visits in East Java Province.

1. INTRODUCTION

Forecasting is an analytical technique aimed at predicting future conditions based on historical data, with a primary focus on identifying patterns in time series data (Petropoulos dkk . 2022). In practice, forecasting plays a strategic role in supporting decision-making processes and policy formulation, both at the individual and organizational levels. Through the analysis of trends over a specific period, forecasting enables the estimation of events that may occur in the future (Annas dkk . 2023).

In time series data analysis, seasonal patterns are often observed, referring to data tendencies that recur regularly within a specific time period. This pattern indicates repetitive movements at fixed intervals, such as monthly or yearly, which are generally influenced by seasonal factors or particular periods. A key characteristic of seasonal time series is the presence of strong autocorrelation at seasonal lags, representing relationships between observations separated by one seasonal cycle according to the number of observations within each period (Kalekar dan Bernard 2004).

The Holt-Winters exponential smoothing method is widely applied to account for seasonal patterns in time series data. As an extension of the Holt method, it incorporates three components: level, trend, and seasonality, forming a triple exponential smoothing approach. This method is effective for forecasting data with trend and seasonal patterns while offering simple implementation and competitive performance compared with more complex models. (Safitri dkk . 2017).

Another widely applied approach in time series analysis is the Autoregressive Integrated Moving Average (ARIMA) model, which addresses trends through its Autoregressive (AR), Integrated (I), and Moving Average (MA) components. For seasonal data, ARIMA can be extended to Seasonal ARIMA (SARIMA) to capture recurring patterns at specific intervals (Khoiriyah dkk . 2023). ARIMA is also advantageous due to its ease of application and flexibility in modeling various time series characteristics, including trend and seasonality (Safitri dkk . 2017).

The tourism sector represents one of the important domains for the application of time series forecasting methods. Tourism is a strategic sector in national economic development and is designated as a leading sector, meaning it serves as a primary driver for the integration of cross-sectoral development programs. Globally, the tourism sector has shown a positive growth trend each year, even under economic pressures. In Indonesia, East Java Province is one of the regions with the highest number of domestic tourist visits (Ayu dkk . 2022).

East Java Province has consistently demonstrated strong performance as a primary destination for domestic tourists. Over the past five years, the province has maintained its top position in the number of domestic tourist visits nationally, with a significantly increasing growth trend (BPS n.d.). This condition makes tourist visit data a relevant object for analysis using time series forecasting methods, particularly in identifying emerging trend and seasonal patterns.

Several previous studies have examined the application of various forecasting methods across different sectors. (Pangestu dkk . 2026) applied the Holt-Winters method to forecast rice production in Indonesia and obtained a MAPE value of 25.72%. Meanwhile, (Junaedi, Damastuti, dan Widodo 2025) applied the SARIMA method to forecast seasonal product sales and achieved very high accuracy, with a MAPE of 1.2%. In the tourism sector, (Bagus, Pradnyana, dan Wisnawa 2025) used the Support Vector Machine (SVM) method to forecast tourist numbers in Bali Province and obtained the lowest MAPE value of 0.0233% in Buleleng Regency.

Although various forecasting methods have been applied in tourism studies, direct comparisons of Holt-Winters and ARIMA for forecasting domestic tourist visits in East Java Province remain limited. The two methods employ different modeling approaches: Holt-Winters focuses on level, trend, and seasonal components through exponential smoothing, whereas ARIMA models temporal dependence through autoregressive, differencing, and moving-average components. Therefore, this study compares the forecasting performance of Holt-Winters and ARIMA using MAE, MAPE, and RMSE to evaluate the suitability of each method for forecasting domestic tourist visits in East Java Province.

This study aims to apply and compare the Holt-Winters and ARIMA methods for forecasting domestic tourist visits in East Java Province. Their forecasting accuracy is evaluated using MAE, MAPE, and RMSE to determine the most effective method. The findings are expected to contribute to the academic and practical development of forecasting methods in the tourism sector.

2. LITERATURE REVIEW

Time series forecasting uses historical observations to estimate future values and identify patterns such as trend, seasonality, cycles, and random components. Thus, selecting a method suited to the data characteristics is crucial for reliable predictions (Cahyono dan Aryanny 2023; Rahayu dan Aswi 2023; Yuliana 2019). One suitable approach is the Holt-Winters method, an extension of exponential smoothing that simultaneously models level, trend, and seasonal patterns.

Exponential smoothing is a forecasting technique that assigns greater weights to more recent observations, making it effective for short-term prediction (Polyvianna, Chumachenko, dan Chumachenko 2019). The Holt-Winters method includes three smoothing parameters. The smoothing parameters α that represents the level, β that represents the trend, and γ that represents the seasonal component. are determined through numerical optimization, with the parameters optimized together with the initial state values to minimize the sum of squared forecasting errors (Hyndman 2014; Navarro dan Navarro

2024). This method consists of an additive model for constant seasonal patterns and a multiplicative model for seasonal patterns that depend on the level of the data (Navarro dan Navarro 2024; Omar dan Kawamukai 2021; Sintiya dkk . 2020), and is capable of producing accurate forecasts for time series data exhibiting both trend and seasonality (Sintiya dkk . 2020) such as monthly tourist visitation data. The formulations are as follows:

a. Multiplicative Holt-Winters Model

The level smoothing is given in Equation (1):

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

Trend smoothing is given in Equation (2):

$$b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1} \tag{2}$$

Seasonal smoothing equation is given in Equation (3):

$$S_t = \gamma\left(\frac{Y_t}{L_t}\right) + (1-\gamma)S_{t-s} \tag{3}$$

Forecast for $m$periods ahead is given in Equation (4):

$$F_{t+m} = (L_t + mb_t)S_{t+m-s} \tag{4}$$

b. Additive Holt-Winters Model

Level smoothing this model is given in Equation (5):

$$L_t = \alpha(Y_t - S_{t-s}) + (1-\alpha)(L_{t-1} + b_{t-1}) \tag{5}$$

Seasonal smoothing this model is given in Equation (6):

$$S_t = \gamma(Y_t - L_t) + (1-\gamma)S_{t-s} \tag{6}$$

Forecast for $m$periods ahead is given in Equation (7):

$$F_{t+m} = L_t + mb_t + S_{t+m-s} \tag{7}$$

with F_{t+m} represents the forecast for period $t+m$, made at the end of period t, while L_t denotes the estimated level estimate at period t, α is the level smoothing constant, $0 < \alpha < 1$, Y_t represents the actual value at period t, b_t denotes the estimated trend at period t, β where $0 < \beta < 1$ serving as the trend smoothing constant, S_t represents the seasonal component at period t, γ where $0 < \gamma < 1$ is the seasonal smoothing constant, m indicates the number of periods ahead to be forecasted and s represents the length of the seasonal cycle.

Initial seasonal indices for multiplicative Holt-Winters (S_k) is given in Equation (8) (Sintiya et al., 2020):

$$S_k = \frac{Y_k}{L_s} \tag{8}$$

and initial seasonal indices for additive Holt-Winters (S_k) is given in Equation (9):

$$S_k = Y_k - L_s \tag{9}$$

with s represents the seasonal length, Ydenotes actual data values, L_s refers to the initial level value and S_k denotes the initial seasonal value.

The Autoregressive Integrated Moving Average (ARIMA) model is a time-series forecasting model developed within the Box–Jenkins framework (Box dan Jenkins 2016). It is commonly represented by the notation ARIMA(*p,d,q*), where *p* denotes the order of the

autoregressive (AR) component, d indicates the degree of differencing required to achieve stationarity, and q represents the order of the moving average (MA) component (Ahmar dan Boj 2020a; Yamak, Yujian, dan Gadosey 2019). Within the Box–Jenkins framework, ARIMA combines autoregressive and moving average components with differencing to model both stationary and non-stationary time-series data (Ahmar 2018).

In general, the AR model describes the relationship between the current value and its past values, and is expressed as follows in Equation (10):

$$Z_t = \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \cdots + \phi_p Z_{t-p} + \alpha_t, t = 1,2,3, \ldots \quad (10)$$

where $\mu'$is a constant, $\phi_p$is the p-th autoregressive parameter, and $\alpha_t$is the error term at time t.

Meanwhile, the MA model captures the influence of past error terms on the current value, and is expressed as follows in Equation (11):

$$Z_t = \alpha_t + \theta_1 \alpha_{t-1} - \theta_2 \alpha_{t-2} - \cdots - \theta_q \alpha_{t-q} \quad (11)$$

The combination of these two forms the ARMA model, which serves as the basis for ARIMA, expressed as follows in Equation (112:

$$\phi_p(B)\dot{Z}_t = \theta_q(B)\alpha_t \quad (12)$$

for the general ARIMA (p, d, q)case, the model can be written as Equation (13):

$$(1 - \phi_1 B - \cdots - \phi_p B^p)(1 - B)^d \dot{Z}_t = (1 - \theta_1 B - \cdots - \theta_q B^q)\alpha_t \quad (13)$$

The implementation of the ARIMA model involves several stages, including model identification through autocorrelation and stationarity analysis, parameter estimation, and diagnostic checking to ensure model adequacy. This includes testing the independence of residuals to satisfy the white noise assumption (Hillmer dan Wei 1991).

Once the model has passed the diagnostic checking stage and is considered adequate, its forecasting performance can be evaluated by measuring the accuracy of the resulting predictions. Evaluation is conducted using forecasting error measures as a method to assess the accuracy of predictions. Several indicators are commonly used to evaluate the performance of forecasting methods, including:

a. Mean Absolute Error (MAE) is a forecasting accuracy measure that quantifies the average absolute difference between actual and predicted values. A lower MAE indicates greater forecasting accuracy (Amansyah dkk . 2024). The MAE is calculated using Equation (14) as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \quad (14)$$

b. Root Mean Squared Error (RMSE) is an evaluation measure used to assess the magnitude of prediction errors by taking the square root of the Mean Squared Error (MSE). RMSE measures the square root of the average squared forecasting errors and gives greater weight to larger errors. Lower RMSE values indicate better forecasting performance (Sinaga dan Irawati 2018). The RMSE is calculated using Equation (15) as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \quad (15)$$

where y_i is actual value, $\hat{y}_i$ is forecasted value, n is the number of observations

c. Mean Absolute Percentage Error (MAPE) is a relative accuracy measure used to determine the average absolute percentage error of a forecast (Sinaga dan Irawati 2018). The MAPE is calculated using Equation (16) as follows::

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \quad (16)$$

MAPE value of less than 10% is classified as very good, a value between 10% and 20% is categorized as good, a value between 20% and 50% is considered fair, and a MAPE value greater than 50% is classified as poor.(Khairina dkk . 2019).

3. METHODOLOGY

This study adopted a quantitative approach to assess and compare the forecasting performance of the Holt-Winters and ARIMA methods in forecasting the number of domestic tourist visits in East Java Province. The analysis utilized secondary data sourced from the Central Bureau of Statistics of East Java Province, consisting of monthly domestic tourist visit data covering the period from January 2021 to December 2025. The data comprised 60 monthly observations, with 54 observations from January 2021 to June 2025 used as the training set and the remaining 6 observations from July to December 2025 used as the testing set. A holdout validation approach was applied, in which each model was fitted using the training data and used to generate six-month-ahead out-of-sample forecasts for the testing period. Forecasting performance was then evaluated by comparing the predicted values with the actual observations using MAE, MAPE, and RMSE. Data were collected using a documentation technique by referring to official reports published by the relevant institution. Data analysis was conducted through several stages based on the forecasting models and equations presented in the literature review. The first stage involved preparing the monthly domestic tourist visit data in East Java Province for the period 2021–2025, followed by descriptive statistical analysis using the mean, median, standard deviation, minimum, and maximum values.

The second stage involved forecasting using the Holt-Winters method by considering the level, trend, and seasonal components. The multiplicative Holt-Winters components were calculated using Equations (1)–(3), with the forecast obtained from Equation (4), while the additive Holt-Winters components and forecast were calculated using Equations (5)–(7). The initial seasonal indices for the multiplicative and additive models were determined using Equations (8) and (9), respectively.

The third stage involved ARIMA modeling following the Box–Jenkins framework. Stationarity was examined using the Augmented Dickey-Fuller (ADF) test, followed by differencing when necessary. Model identification was performed using ACF and PACF plots to determine the values of p, d, and q. The AR component was formulated based on Equation (10), the MA component based on Equation (11), the ARMA model based on Equation (12), and the general ARIMA model based on Equation (13). The selected models were then estimated and subjected to diagnostic checking through residual analysis to assess the white-noise assumption.

The final stage involved evaluating and comparing forecasting accuracy using MAE, RMSE, and MAPE based on Equations (14)–(16), respectively. Lower error values indicate better forecasting accuracy. The results were then interpreted to compare the forecasting performance of the Holt-Winters and ARIMA methods and to formulate conclusions regarding domestic tourist visits in East Java Province.

4. RESULT

Descriptive analysis was conducted to provide an overall description of the number of domestic tourist visits in East Java Province. Data processing and analysis were performed using the R programming language as the primary computational environment. The dataset comprises monthly observations of domestic tourist visits in East Java Province covering the period from 2021 to 2025, sourced from the Central Bureau of Statistics (BPS).

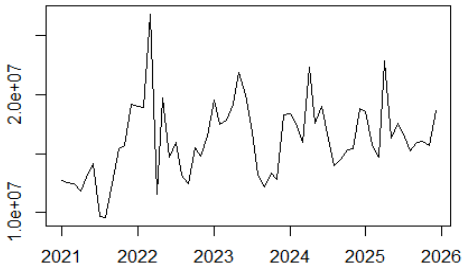

Figure 1. Plot of the Number of Domestic Tourists in East Java in 2021-2025

The plotted graph of tourist numbers illustrates the development of domestic tourist visits over the period from 2021 to 2025 based on the Figure 1. In general, the data exhibit fluctuations over time. At the beginning of 2021, the number of tourists was relatively low, followed by a significant increase, reaching a peak around early 2022. After this period, the number of tourists declined sharply; however, it subsequently showed irregular upward and downward movements until 2025.

In addition, the pattern of data movement indicates the presence of a seasonal pattern, as evidenced by recurring increases in tourist numbers during certain periods each year. This suggests that tourist visits tend to rise at specific times, possibly influenced by holiday seasons or particular tourism activities. Overall, the data do not yet exhibit strong stability, as considerable variation is still observed across periods.

Descriptive analysis is also conducted by examining the statistical values of the tourist data over the observation period. Descriptive statistics are used to provide a general overview of the data characteristics, including minimum, maximum, mean, and standard deviation values. The results of the descriptive statistical analysis of domestic tourist data are presented in the following table.

The number of domestic tourist visits in East Java Province during the period 2021 to 2025 has a minimum value of 9588986 visits and a maximum value of 26811651 visits. The average (mean) number of domestic tourist visits is recorded at 16146428 visits, with a standard deviation of 3225387. These results indicate that the number of domestic tourist visits in East Java Province exhibits considerable variation over time. The observed trend and recurring seasonal fluctuations indicate that the data are suitable for forecasting using a method that can accommodate both trend and seasonality, such as Holt-Winters, while ARIMA provides an alternative approach based on the temporal dependence structure of the series.

The modeling results using the Holt-Winters method indicate that the resulting model consists of additive trend and seasonal components. The estimated smoothing parameters are $\alpha = 0.0767$, $\beta = 0.1493$, and $\gamma = 1.0000$. The relatively small value of α suggests that the level component changes gradually, while the value of β indicates that the trend is relatively stable. Meanwhile, the value of $\gamma = 1.0000$ indicates that the seasonal component is given a full weight when being updated based on new observations; however, this value should not be interpreted as a measure of the magnitude or strength of seasonality.

Overall, the Holt-Winters method is able to effectively capture both trend and seasonal patterns in the tourist data. The dominance of the seasonal component in the model indicates that variations in the number of tourists are highly influenced by seasonal factors. Therefore, this method is considered appropriate for forecasting tourism data that exhibit recurring periodic patterns. In addition to the Holt-Winters method, the ARIMA model is applied as an alternative forecasting approach to capture the temporal dependence and underlying patterns in the time series data. Unlike Holt-Winters, which explicitly incorporates trend and seasonal components, ARIMA focuses on the autoregressive and moving average structures of the series and requires the data to satisfy the stationarity assumption. Therefore, stationarity testing is performed as an initial step before identifying and estimating the ARIMA model.

Stationarity testing is performed to determine whether the time series satisfies the assumption of mean stationarity. The Augmented Dickey-Fuller (ADF) test is applied by comparing its p-value with the 5% significance level. A p-value below 0.05 indicates that the null hypothesis of a unit root can be rejected, suggesting that the series is stationary in the mean. The ADF test produced a test statistic of -3.4284 using 3 lags, with an exact p-value of 0.06075. Since the p-value is greater than 0.05, the null hypothesis of a unit root cannot be rejected at the 5% significance level. Therefore, the time series is not considered stationary in the mean at the 5% significance level, indicating that differencing is required before proceeding to the ARIMA model identification stage.

Since the original time series was not stationary at the 5% significance level, first-order differencing was performed to achieve stationarity. The first differencing was applied to the training data, and the stationarity of the transformed series was subsequently assessed using the Augmented Dickey-Fuller (ADF) test. The results showed an ADF test statistic of -3.9686 with a lag order of 3 and a p-value of 0.01762. Since the p-value is less than 0.05, the null hypothesis of a unit root is rejected at the 5% significance level. Therefore, the first-differenced series can be considered stationary in the mean, indicating that the data are suitable for proceeding to the ARIMA model identification stage.

ARIMA model identification aims to determine the appropriate model order by analyzing the dependency structure among observations in time series data. Plots of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) for stationary data are used to identify these autocorrelation patterns, which then serve as the basis for determining the ARIMA parameter order in the subsequent modeling stage.

(a) (b)

Figure 2. Plot of Domestic Tourist Visit Data in East Java Province; (a) ACF Plot, (b) PACF Plot

Based on the ACF and PACF plots of the first-differenced data on the Figure 2, three candidate ARIMA models were identified. The ACF plot shows a significant spike at lag 1, suggesting a possible moving average (MA) component of order 1, so ARIMA (0,1,1) was considered. Meanwhile, the PACF plot shows a significant spike at lag 1, suggesting an

autoregressive (AR) component of order 1, leading to ARIMA (1,1,0). In addition, ARIMA(1,1,1) was included to represent a model combining both AR and MA components at lag 1. Therefore, these three models were selected for further parameter estimation and evaluation to determine the most appropriate model.

After identifying the candidate ARIMA models based on the ACF and PACF plots, the models were further compared to determine the most appropriate specification for the domestic tourist visit data. The comparison was conducted using three model selection criteria, namely the Akaike Information Criterion (AIC), corrected Akaike Information Criterion (AICc), and Bayesian Information Criterion (BIC). Lower values in these criteria indicate a better balance between model fit and complexity. The comparison results of the three candidate models are presented in Table 1.

Table 1. Comparison of Candidate ARIMA Models Based on AIC, AICc, and BIC

Model	AIC	AICc	BIC
ARIMA(0,1,1)	1744.126	1744.366	1748.067
ARIMA(1,1,0)	1743.436	1743.676	1747.377
ARIMA(1,1,1)	1744.977	1745.467	1750.888

The comparison results on the Table 1 show that ARIMA(1,1,0) has the lowest values across all three model selection criteria, with an AIC of 1743.436, AICc of 1743.676, and BIC of 1747.377. These values are lower than those obtained from ARIMA(0,1,1) and ARIMA(1,1,1). Therefore, based on the AIC, AICc, and BIC criteria, ARIMA(1,1,0) was selected as the preferred candidate model for forecasting domestic tourist visits in East Java Province. The selected model was subsequently subjected to diagnostic checking to assess whether the residuals satisfy the required assumptions before forecasting.

After obtaining the ARIMA model, parameter estimation is conducted by testing the significance of the model parameters. The significance test is applied to the selected tentative ARIMA model. The hypotheses used in this parameter testing are as follows:

H_0: Parameter is not significant

H_1: Parameter is significant

at a significance level of $\alpha = 0.05$, the rejection region is defined as rejecting H_0 if $| t | > t_{\alpha,df=n-p}$ or if the p-value is less than 0.05.

Table 2. Significance Test of the Model

Parameter	Estimate	Std. Eror	p-value
AR(1)	-0.5078	0.1160	< 0.001

After obtaining the appropriate ARIMA model, the next step is to perform model diagnostics by analyzing the residuals. This analysis aims to ensure that the residuals generated from the model are random. The test is conducted using an independence test to determine whether the residuals are independent (white noise).

The hypotheses used in testing residual independence are as follows:

H_0:Residuals are independent (no autocorrelation)

H_1:Residuals are not independent (there is autocorrelation)

at a significance level of $\alpha = 0.05$, H_0 is rejected if the p-value is less than 0.05. If H_0 is not rejected, the residuals can be considered independent, indicating that the ARIMA model is adequate for forecasting.

Table 3. Ljung–Box Test Results

Component	Value
Model	ARIMA (1,1,0)
Q Statistic	6.1303
Degrees of Freedom (df)	9
p-value	0.7268
Lag Used	10

Based on the Table 3, the Ljung–Box Test shows that the p-value is 0.7268, which is greater than 0.05. Therefore, the null hypothesis (H_0) is not rejected, indicating that the residuals are not significantly correlated (independent). Thus, the residuals satisfy the white noise assumption, suggesting that the model is adequate for forecasting.

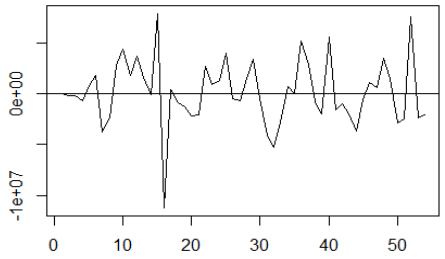

Figure 3. Residual time-series plot of the selected ARIMA model

The stability of the residual variance was assessed using the residual time-series plot. As shown in Figure 3, the residuals fluctuate around zero without a clear systematic pattern in their spread over time. Although several relatively large residuals are observed at some time points, there is no clear evidence of an increasing or decreasing variance pattern. Thus, the residual variance can be considered relatively stable over the observation period.

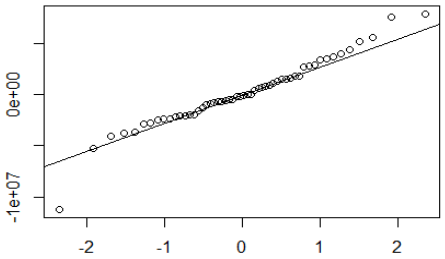

Figure 4. Normal Q-Q plot of the selected ARIMA model

The approximate normality of the residuals was assessed using the histogram and normal Q-Q plot. As shown in Figure 4, most residuals follow the theoretical normal line, particularly in the central part of the distribution. However, some deviations are observed at the tails, indicating the presence of several relatively extreme residuals. Therefore, the residuals can be considered approximately normally distributed, although the normality assumption is not exact.

Overall, the diagnostic results indicate that the selected ARIMA(1,1,0) model has no significant residual autocorrelation, relatively stable residual variance, and approximately normally distributed residuals. These results indicate that the model provides an adequate basis for forecasting the number of domestic tourist visits. After applying the Holt-Winters and ARIMA methods, their forecasting accuracy was evaluated and compared. Model evaluation is conducted using forecasting error measures, namely: MAE that measures the average absolute deviation between actual and forecasted values, RMSE that represents the square root of the mean squared error and is expressed in the same unit as the observed data,

and MAPE that indicates the average percentage error. Lower MAE, RMSE, and MAPE values indicate better forecasting performance.

Table 4. Comparison of Best Model Evaluation

Method	MAE	RMSE	MAPE
Holt-Winters	644301.5	770807.3	4.0561
ARIMA (1,1,0)	1226200	1341644	7.5642

Based on Table 4, the Holt-Winters method has smaller MAE, RMSE, and MAPE values compared to the ARIMA (1,1,0) model, indicating better performance in minimizing absolute prediction errors. Therefore, the Holt-Winters method is selected as the best model. Based on the selected best model, the forecasting results are presented in Table 5 and Figure 5 as follows:

Table 5. Forecast Results of Domestic Tourist Visits in East Java Province

Period	Forecast
Jan 2026	18432606
Feb 2026	15817486
Mar 2026	14807423
Apr 2026	22907622
May 2026	16517153
Jun 2026	17914458
Jul 2026	17093456
Aug 2026	15582528
Sep 2026	16235448
Oct 2026	16356136
Nov 2026	15981861
Dec 2026	18917545

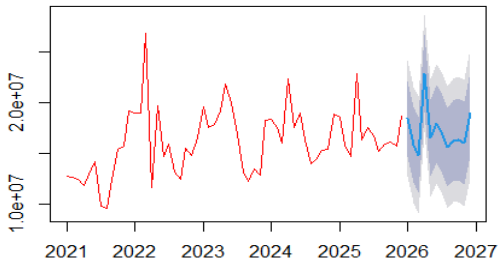

Figure 5. Forecasting Graph of Domestic Tourist Visits in East Java Province for 2026

5. CONCLUSION

Based on the analysis of domestic tourist visits in East Java Province from 2021 to 2025, the data exhibit considerable fluctuations and a recurring seasonal pattern. The Holt-Winters and ARIMA methods were applied to forecast tourist visits, with ARIMA(1,1,0) selected based on the lowest AIC, AICc, and BIC values and satisfying the main residual diagnostic assumptions. However, based on the accuracy comparison, the Holt-Winters method produces lower MAE, RMSE, and MAPE values than the ARIMA (1,1,0) model. Therefore, the Holt-Winters method is selected as the best forecasting model in this study. Furthermore, the forecasting results for 2026 indicate fluctuations in the number of domestic tourist visits throughout the year, with relatively higher visits at the beginning and toward the end of the year, consistent with the seasonal pattern observed in the historical data.

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