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Damped Trend Exponential Smoothing and Holt-Winters in Predicting the Number of Airplane Passengers at Kualanamu Airport

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ABSTRACT

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Airplanes are one of the most frequently chosen modes of transportation by Indonesians today. Kualanamu Airport is one of the busiest airports in terms of the number of passengers. The number of airplane passengers often fluctuates, increasing and decreasing, so an analysis method is required to predict the number of passengers. This study uses the Double Exponential Smoothing Damped Trend and Multiplicative Holt-Winters models. The number of Kualanamu Airport domestic airplane passengers from January 2006 to December 2023 was used as research data. The best model is then used to forecast the number of Kualanamu Airport domestic airplane passengers for 12 periods from the last data used. The results showed that the Multiplicative Holt-Winters model with smoothing parameters α=0.573; $\boldsymbol{\beta} = \mathbf{0.000648}$ and $\boldsymbol{\gamma} = \mathbf{0.143}$ obtained smaller (Mean Absolute Error) MAE and (Mean Square Error) MSE values of 21415.556 and 961525264.508, compared to the Double Exponential Smoothing Damped Trend model with smoothing parameters, $\boldsymbol{\alpha} = \mathbf{0.56}$; $\boldsymbol{\beta} = \mathbf{0.0001}$, and $\boldsymbol{\phi} = \mathbf{0.98}$ which obtained MAE and MSE values of 23612.461 and 1061042411.507 in predicting the number of domestic aircraft passengers at Kualanamu Airport. Forecasting accuracy for the next 12 periods using Holt-Winters Exponential Smoothing produces a MAPE value of 9.2%. It shows the accuracy of forecasting in the very good category.

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1. Introduction

Airplanes are one of the most frequently chosen modes of transportation by the Indonesian people today. This can happen because airplanes are one of the transportation methods used to support business and tourism activities **[1]**. In addition, the reason airplanes are also the choice of the community, especially at certain *events*, is because airplanes are considered to have the advantage of flexibility in choosing airlines and departure times, capacity that can be adjusted to demand, and the breadth of flight connectivity that connects every province in Indonesia **[2]**.

In Indonesia, there are several international airports as well as the busiest airports. Reporting from **[3]**, there are five busiest airports in terms of the number of passengers throughout 2023 in Indonesia. One of them is Kualanamu Airport. Throughout 2023, Kualanamu Airport ranks second with 7.39 million passengers under Soekarno-Hatta Airport with 50.96 million passengers and followed by Halim Perdana Kusuma Airport, Sultan Syarif Kasim II Airport, and Sultan Mahmud Badaruddin II Airport with 3.79 million; 2.76 million; and 2.75 million passengers respectively. Based on these considerations, Kualanamu Airport was chosen as the subject of this research due to its strategic role as one of the busiest airports in Indonesia. Moreover, Kualanamu Airport holds a crucial role as a primary aviation hub in North Sumatra, with dynamic passenger growth, making it an interesting case study for optimizing operational planning.

Previous studies related to Kualanamu Airport have generally focused on analyzing operational performance, passenger satisfaction, airport service efficiency, and economic impact. For example, research conducted by **[4][5]** examined passenger satisfaction at Kualanamu Airport regarding its services and facilities. Another study by **[6]** discussed the impact of Kualanamu Airport on the socioeconomic changes in the surrounding community. However, studies that specifically analyze passenger forecasting using time series methods remain very limited. This research aims to fill that gap by providing insights into forecasting, which can support airport management in making data-driven decisions.

The number of airplane passengers in Indonesia often experiences fluctuations in both increases and decreases **[7]**. The increase and decrease in airplane passengers in Indonesia usually occur at certain *events* or conditions. It can be seen that the number of airplane passengers declined in early 2020 when the COVID-19 pandemic began in Indonesia. Throughout January-March 2020, PT Angkasa Pura II, a State-Owned Enterprise (BUMN) in charge of managing several airports in Indonesia, recorded a decrease of 20.79 million airplane passengers or a decrease of around 4.84% compared to January-March 2019.

In addition, there was also a decrease in the number of domestic airplane passengers that occurred in January 2024 by 4.8 million, or about 13.76% lower than in December 2023. However, there was an increase in the number of international airplane passengers by 1.5 million or about 0.41% at the same time **[8]**. Based on the various fluctuations in the increase and decrease in the number of airplane passengers, an analysis method is needed that can be used to predict the number of airplane passengers in the future.

Forecasting is the art or science of estimating events in the future. The forecasting process is carried out by taking historical data and projecting the data in the future with the help of mathematical models **[9]**. In forecasting, especially with time series, the components or pattern elements contained in the data play a very important role in the selection of forecasting methods and the forecasting results. Data with only an upward or downward trend level component tends to be predicted using methods whose models are built only with the trend component. Double Exponential Smoothing (DES) and ARIMA are some forecasting models whose models are built with a trend component. However, these methods often experience overforecasting or underforecasting data with uptrend and downtrend components or trends whose increase or decrease is significantly slowed or accelerated. This causes the results of the forecasting values from these methods to be often much larger or smaller than the actual data.

Damped Trend Exponential Smoothing is an extension of the method used in Exponential Smoothing. It was originally a modification of DES. DES that has been modified with a Damped Trend is called a Double Exponential Smoothing Damped Trend (DESDT). DESDT is considered much better than DES because it can model trends that slow down or change. Previous research with DESDT has been conducted several times, one of which was conducted by **[10]** to forecast Gold Prices in Indonesia and obtained a MAPE of 0.49%.

Holt-Winters is an exponential smoothing method used for time series data containing trend and seasonal components elements. Researchers often use this method because it is considered to have high accuracy for data with seasonal patterns. Some previous studies that used Holt-Winters, such as those conducted by **[11],** to predict the number of foreign tourists visiting Indonesia obtained a MAPE of 0.938%. Furthermore, research was conducted by **[12]** to forecast Indonesian Red Onion Production and obtained a MAPE of 13.469%.

Based on the above explanation, this study takes a different approach from previous research **[10][11][12]** by specifically focusing on forecasting using the Damped Trend Exponential Smoothing and Holt-Winters methods. This study aims to forecast the number of air passengers at Kualanamu Airport using these two methods. Both methods were chosen for their ability to handle seasonal patterns and trend changes in passenger volume data. Damped Trend Exponential Smoothing is capable of capturing long-term or sensitive trends while avoiding overly extreme predictions, whereas Holt-Winters is more effective in dealing with recurring seasonal patterns. By comparing these two methods, this study is expected to identify the most appropriate forecasting model to support Kualanamu Airport's management in making data-driven decisions.

Furthermore, This study analyzed the forecasting of the number of airplane passengers at Kualanamu Airport using Damped Trend Exponential Smoothing and Holt-Winters. The best method obtained was then used to forecast the number of airplane passengers for the next year. The best method was chosen by comparing the smallest Mean Absolute Error (MAE) and Mean Square Error (MSE) accuracy values of the two methods **[13][14]**.

2. Research Methods

2.1. Damped Trend Exponential Smoothing

The Damped Trend Exponential Smoothing method was originally developed by Gardner & McKenzie in 1985 to develop a variant of Holt's Double Exponential Smoothing (Holt's DES). This model was introduced with a damping mechanism to prevent the trend estimate from becoming too sensitive to data fluctuations **[10]**. The addition of a damped trend (ϕ) to Holt's Double Exponential Smoothing is intended because of the frequent occurrence of over-forecasting or under-forecasting (forecasting results are much larger or smaller than the actual data), which can be caused by fluctuations in decline or increase that are so significant or vice versa. This research used a damped trend (ϕ) on Holt's Double Exponential Smoothing. The following is the equation used in Double Exponential Smoothing Damped Trend **[10]**:

$$L_t = \alpha X_t + (1-\alpha)(L_{t-1} + \phi b_{t-1}) \tag{1}$$

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

$$F_{t+m} = L_t + (\phi^1 + \phi^2 + \cdots + \phi^m)(b_t)m \tag{3}$$

Where:

X_t = Actual data of period-t
L_t and b_t = Level smoothing and trend smoothing for period-t
α, β, andϕ = Smoothing parameters for level, trend, and damped trend with values between 0 and 1
m = Period of data to be forecasted
F_{t+m} = Forecasting results at m period ahead of period-t

The following are the steps of the Damped Trend Exponential Smoothing method used in this study:

1. Determine the initial values for α, β, and ϕ explicitly, which will be used in the initial calculations.
2. Set the initial values for the level smoothing component (L_t) and the trend smoothing component (b_t).
3. Calculate the forecast (F_{t+m}) for one period ahead from the initial set-value period.
4. Perform calculations for the level smoothing (L_t), trend smoothing (b_t), and the one-period-ahead forecast (F_{t+m}) for the subsequent periods using the equations described in Subsection 2.1.
5. Calculate the Root Mean Squared Error (RMSE) from the initial calculation of the Damped Trend Exponential Smoothing method.
6. Determine the optimal values of α, β, and ϕ by finding the minimum RMSE through iterative trial-and-error calculations with the assistance of software.
7. Perform the optimal forecasting using the Damped Trend Exponential Smoothing method once the optimal values of α, β, and ϕ have been obtained.
8. Create a plot comparing the actual values with the forecasted values.

2.2. Holt-Winters Exponential Smoothing

The Holt-Winters Exponential Smoothing (HWES) method is a smoothing method that is based on data having trend and seasonal components [15]. This method was originally developed by P. R. Winters in 1965 by developing the Holt method by adding a seasonal component. In [15], it is explained that *time series* data with trend and seasonal elements is suitable for the Holt-Winters method, which has three parameter weights in the process. The Holt-Winters method is divided into two types [16][17], namely:

1. Multiplicative Holt-Winters (MHW), is a Holt-Winters model used on data that tends to have seasonal variations that experience varying increases or decreases.
2. Additive Holt-Winters (AHW), is a Holt-Winters model used on data that tends to have constant seasonal variations.

Here is the equation for Multiplicative Holt Winter (MHW) [17][18].

$$L_t = \alpha\left(\frac{X_t}{S_{t-s}}\right) + (1-\alpha)(L_{t-1} + b_{t-1}) \tag{4}$$

$$b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1} \tag{5}$$

$$S_t = \gamma\left(\frac{X_t}{L_t}\right) + (1-\gamma)S_{t-s} \tag{6}$$

$$F_{t+m} = (L_t + b_t m)S_{t-s+m} \tag{7}$$

Next is the equation for Additive Holt-Winters (AHW) [17][18].

$$L_t = \alpha(X_t - S_{t-s}) + (1-\alpha)(L_{t-1} + b_{t-1}) \tag{8}$$

$$b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1} \tag{9}$$

$$S_t = \gamma\,(X_t - L_t) + (1-\gamma)S_{t-s} \tag{10}$$

$$F_{t+m} = (L_t + b_t m + S_{t-s+m}) \tag{11}$$

Description of the MWH and AWH equations:

Xt = Actual data of period-t
L_t, b_t, and S_t = Level, trend, and seasonal smoothing of period-t
α, β, and γ = Level, trend, and season smoothing parameters with values between 0 and 1
m = Period of data to be forecasted
s = Season length.
F_{t+m} = Prediction results at m period ahead of period- t

The following are the steps of the Holt-Winters Exponential Smoothing method used in this study:

1. Determine the initial values for α, β, and γ explicitly to be used in the initial calculation.
2. Set the initial values for level smoothing (L_t), trend smoothing (b_t), and seasonal smoothing (S_t).
3. Calculate the forecast (F_{t+m}) for one period ahead from the set-value period.
4. Perform calculations for the level smoothing (L_t), trend smoothing (b_t), seasonal smoothing (S_t), and the forecast for the next period (F_{t+m}) using the equations presented in Subsection 2.2.
5. Calculate the Root Mean Squared Error (RMSE) from the initial Holt-Winters Exponential Smoothing calculation.
6. Determine the optimal values of α, β, and γ by finding the minimum RMSE through iterative recalculations using the Holt-Winters Exponential Smoothing method with the help of software and a trial-and-error technique.
7. Perform the optimal forecasting using the Holt-Winters Exponential Smoothing method after obtaining the optimal values of α, β, and γ.

8. Create a plot comparing the actual values with the forecasted values.

2.3. Research Procedures

The research procedures used in this study are as follows:

1. Collecting data from the official BPS (Central Bureau of Statistics) website and inputting the data into the software.
2. Conducting data description.
3. Performing trend and seasonality assumption tests:
   a. Testing data stationarity using the Box-Cox transformation and Augmented Dickey-Fuller (ADF) test.
   b. Identifying the seasonal period contained in the data using the Autocorrelation Function (ACF).
4. Conducting calculations using the Damped Trend Exponential Smoothing and Holt-Winters Exponential Smoothing methods.
5. Calculating and comparing the error values of both methods using Mean Absolute Error (MAE) and Mean Square Error (MSE).
6. Performing forecasting using the best method.
7. Calculating the accuracy of the forecast results using Mean Absolute Percentage Error (MAPE).
8. Drawing conclusions or interpretations.

3. Results And Discussion

3.1. Data Description

In this study, data on the number of passengers on domestic aircraft departures at Kualanamu airport were obtained through the official website of the Central Statistics Agency (BPS) from January 2006 to December 2023 [19]. The data is presented in descriptive statistics, as shown in Table 1, and a graphical plot is made in Figure 1. Its characteristics are analyzed as follows.

Table 1. Descriptive Statistics

Minimal	Q_1	Median	Mean	Q_3	Maximum
3593	169338	225334	218773	267850	384004

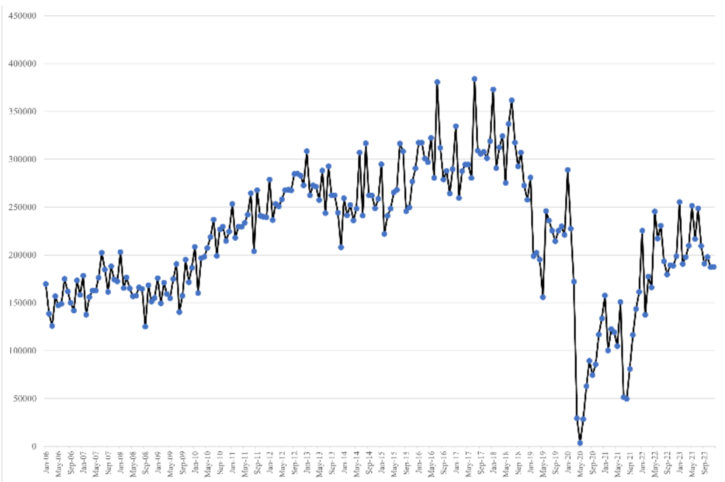

Figure 1. Plot of Domestic Airplane Passenger Data 2006-2023
Data source: Central Bureau of Statistics

In Figure 1, the number of passenger data fluctuates in several segments. One of them can be seen from September 2008 to July 2017, when the data tends to experience an upward trend. However, in some segments, the data tends to experience a significant downward trend, such as from January 2018 to May 2020. Then, the data experienced an upward trend from June 2020 to July 2023. In addition, the data plot shows the influence of seasonal patterns, which can be seen in the data, which tend to experience repeated peaks and lows in certain months. Thus, this indicates that the Damped Trend Exponential Smoothing and Holt-Winters methods can be appropriate approaches for forecasting.

3.2. Identifying Data Stationarity

Data stationarity was identified both in variance and mean to determine the elements of the components that make up the data. In identifying data stationarity, the first step is to identify whether the data is stationary in variance or not. Box-Cox test is performed on domestic airplane passenger data to determine the stationarity of the data in variance, and the results obtained are shown in **Table 2**.

Table 2. Box-Cox Transformation Results

Test	Lambda ($\boldsymbol{\lambda}$)
Box-Cox Test	1.232

Based on **Table 2**, it can be seen that the lambda value of ($\boldsymbol{\lambda}$) based on the test results is 1.232. The lambda value is close and can be rounded to 1.00, which indicates that the data is stationary in variance **[20]**. The next step was to identify the stationarity of the data in the mean. The ADF (Augmented Dickey-Fuller) test was conducted to determine the stationarity of the data in the mean. The results are obtained as in data, and the results are obtained as in **Table 3**.

Table 3. ADF Test Results

Test	p-value
Augmented Dickey Fuller-Test	0.651

In the ADF Test, decision-making is based on the p-value. Where if the p-value $< \mathbf{0.05}$, then the data is said to be stationary in the mean **[14]**. Based on this, it can be seen in **Table 3** that the p-value$= \mathbf{0.651}$, so it can be concluded that the data is not stationary in the mean because the p-value $\geq \mathbf{0.05}$. Based on the results of the Box-Cox test and ADF test, it can be seen that the domestic airplane passenger data is not stationary because it is only stationary in variance but not stationary on average. The results of this non-stationary data also indicate that the data contains an element of trend or seasonality.

3.3. Autocorrelation Function (ACF)

The ACF plot identifies the trend and seasonal patterns of the data on the number of passengers on domestic airplane departures, as follows.

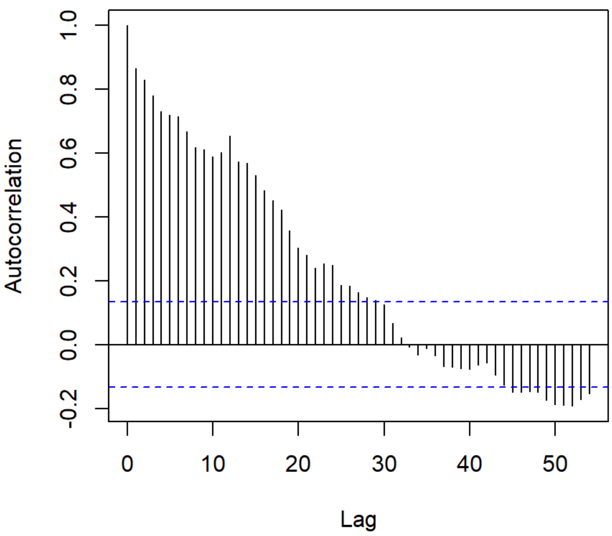

Figure 2. Plot of ACF Result Data

Based on the ACF plot in **Figure 2**, it is clear that the domestic airplane passenger data is not stationary because the ACF plot value does not drop to near zero quickly after the first lags onwards but experiences a significant value in the early lags and decreases gradually which also indicates that the data contains a trend element component. In addition, the ACF plot also shows the presence of autocorrelation, which remains significant at certain recurring lags. The value at certain lags tends to fall slowly and gradually, such as at lags 1, 12, 24, and so on, which indicates a seasonal pattern in the data with a season length of 12 ($\boldsymbol{s} = \mathbf{12}$).

3.4. Calculation of Damped Trend Exponential Smoothing Method

Damped Trend Exponential Smoothing is an Exponential Smoothing method that adds a damped trend parameter ($\boldsymbol{\phi}$). This method is used to smooth data with significant or extreme trend fluctuations, such as the data shown in **Figure 1**. In this study, the damped trend parameter ($\boldsymbol{\phi}$) was used in Holt's Double Exponential Smoothing with calculations using equations (1), (2), and (3).

1. The initial step in this calculation stage was to determine the initial values for the parameters $\alpha, \beta,$ and ϕ arbitrarily with the condition that the parameter values are between 0 and 1. At this initial stage, the values of the smoothing parameters, namely $\alpha = 0.6$, $\beta = 0.3$, and $\phi = 0.7$, were used.
2. The next step was determining the initial set-value in period-t $= 2$ for level smoothing value(L_2) and trend smoothing value (b_2). Then, the prediction results for 1 period ahead (F_{2+1}) for-t $= 2$ were calculated. For the initial set-value of level smoothing, the calculation $\mathrm{L}_2 = \mathrm{X}_2$ was used, and for the set-value $\mathrm{b}_2 = \mathrm{X}_2 - \mathrm{X}_1$, the following calculation was obtained.

$$L_2 = X_2 = 138623$$

$$b_2 = X_2 - X_1 = 138623 - 169652 \; = -31029$$

$$F_{2+1} = \; F_3 = L_2 + (\phi^1)(b_2)1 = 138623 + (0.71)(-31029)1 = 116903.7$$

3. Calculate the level smoothing value (S_t), the trend smoothing value(b_t), and the prediction result 1 period ahead (F_{t+1}) when period t = 3.

$$L_3 = \alpha X_3 + (1-\alpha)(L_2 + \phi b_2) = 0.6(125954) + (1-0.6)(138623 + 0.7(-31029))$$
$$= 122333.48$$

$$b_3 = \beta(L_3 - L_2) + (1-\beta)\phi b_2 = 0.3(122333.48 - 138623) + (1 - 0{,}3).7(-31029)$$
$$= -20091.066$$

$$F_{3+1} = F_4 = L_3 + (\phi^1)(b_3)1 = 122333.48 + (0.71)(-20091.066)1$$
$$= 108269.734$$

The above calculation is performed for the next data for each period $= 3, 4, \; \ldots \; ,216$ until the predicted value forF_{216} is obtained.

4. After obtaining the first calculation of the DES Damped Trend model, repeated calculation iterations are carried out using RStudio software to get the optimum value of α, β, and ϕ by comparing the RMSE value of each calculation result.
5. In this step, the optimum values of the parameters, namely $\alpha = 0.56, \beta = 0.0001$, and $\phi == \; 0.98$, with a minimum RMSE value of 32489.21, are obtained after repeated iterations of calculations.

Furthermore, after obtaining the optimum calculation results from the DES Damped Trend calculation, a comparison plot is presented in **Figure 3** for the actual data and the value of the forecasting calculation results from the DES Damped Trend.

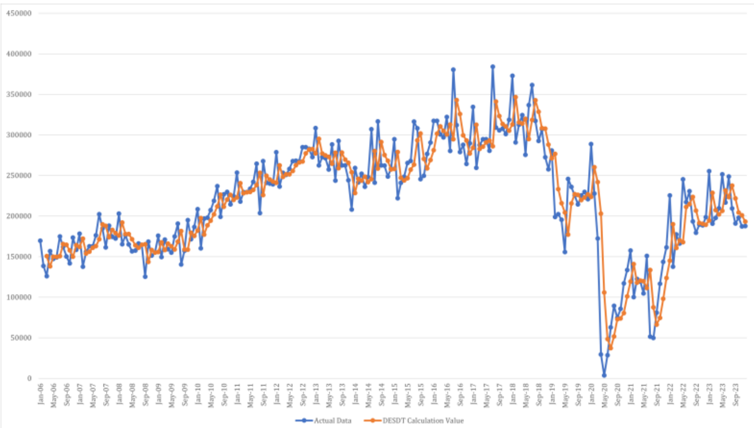

Figure 3. Comparison Plot of Actual Data and DESDT Calculation

3.5. Calculation of Holt-Winters Exponential Smoothing Method

Holt-Winters is a method based on data with trend and seasonality elements. In this method, three smoothing weighting parameters are used, namely alpha (α), beta (β), and gamma (γ). The Holt-Winters method is divided into two models, namely Multiplicative and Additive. Based on **Figure 1**, it can be observed that the data tends to exhibit seasonal variations with fluctuating increases and decreases. Therefore, a Multiplicative model is used, with calculations based on equations (4), (5), (6), and (7).

1. The initial step in this calculation stage was to determine the initial values for the parameters α, β, and γ arbitrarily with the condition that the parameter values are between 0 and 1. At this initial stage, the values of the smoothing parameters, namely $\alpha = 0.5$, $\beta = 0.1$, and $\gamma = 0.2$, were used.
2. The next step was to determine the initial set values for level smoothing(L_t), trend smoothing(b_t), and seasonal smoothing(S_t). To determine the initial set value of level smoothing(L_s), an average calculation of the data $t = 1, 2, \dots, 12$ was used. This is because the data in this study tends to recur every 12 months, so the value $s = 12$ was used. Then, the calculation for the initial set value is (L_{12}), as follows.

$$L_{12} = \frac{\sum_{t=1}^{12} X_t}{12} = \frac{1848195}{12} = 154016.25$$

3. Determining the initial set-value for the trend smoothing value(b_t) at time t = 12. A calculation was used by subtracting each data in the second season from each data in the first season, dividing by the number of seasons($s = 12$), and then averaging. Then the following calculation was obtained

$$b_{12} = \frac{\sum_{t=1}^{12}\left(\frac{X_{12+t} - X_t}{12}\right)}{12} = \frac{17444.917}{12} = 1453.743$$

4. Determine the initial set value for the seasonal smoothing initial value (S_t). Based on the data in this study, there tends to be a recurrence every 12 months, so the value $s = 12$ was used. The initial value of seasonal smoothing (S_t) starts during the period $t = 1, 2, \dots, 12$ by dividing each data point in the first season by the average data point in the first season. The calculation is obtained as follows.

$$S_1 = \frac{X_1}{\frac{1}{12}\sum_{t=1}^{12} X_t} = \frac{169652}{154016.25} = 1.102$$
$$S_2 = \frac{X_2}{\frac{1}{12}\sum_{t=1}^{12} X_t} = \frac{138623}{154016.25} = 0.900$$
$$S_3 = \frac{X_3}{\frac{1}{12}\sum_{t=1}^{12} X_t} = \frac{125954}{154016.25} = 0.818$$
$$\vdots$$
$$S_{12} = \frac{X_{12}}{\frac{1}{12}\sum_{t=1}^{12} X_t} = \frac{158444}{154016.25} = 1.029$$

5. After obtaining the set value for each smoothing value, the prediction calculation for the next 1 period (F_{t+1}) was carried out during the period $t = 12$ as follows.

$$F_{12+1} = F_{13} = (L_{12} + (b_{12})1)S_1 = (154016.25 + (1453.743)1)1{,}102 = 171253.327$$

6. Furthermore, the level smoothing value (L_t), trend smoothing value (b_t), season smoothing value (S_t), and prediction results 1 period ahead (F_{t+1}) at the period $t = 13$ were calculated.

$$L_{13} = \alpha\left(\frac{X_{13}}{S_1}\right) + (1-\alpha)(L_{12} + b_{12}) = 0{,}5\left(\frac{178255}{1.102}\right) + (1 - 0.5)(154106.25 + 1453.743)$$
$$= 158648.18$$
$$b_{13} = \beta(L_{13} - L_{12}) + (1-\beta)b_{12} = 0.1(158648.18 - 154016.25) + (1 - 0.1)1453.743$$
$$= 1771.562$$
$$F_{3+1} = F_{14} = (L_{13} + (b_{13})1)S_2 = (158648.18 + (1771.562)1)0.900$$
$$= 144368.49$$

The above calculation was performed for the next data for each period $t = 3, 4, \dots, 216$ until the predicted value for F_{216} was obtained.

7. After obtaining the first calculation of the Multiplicative Holt-Winters model, repeated calculation iterations were carried out using RStudio software to get the optimum value of α, β, and γ by comparing the RMSE value of each calculation result.
8. In this step, the optimum values of the parameters, namely $\alpha = 0.573, \beta = 0.000648$, and $\gamma = 0.143$, with a minimum RMSE value of 31008.471, are obtained after repeated iterations of calculation.

Furthermore, after obtaining the optimum calculation results from the Multiplicative Holt-Winters calculation, **Figure 4** presents a comparison plot of actual data and forecasting calculation results from the Multiplicative Holt-Winters calculation.

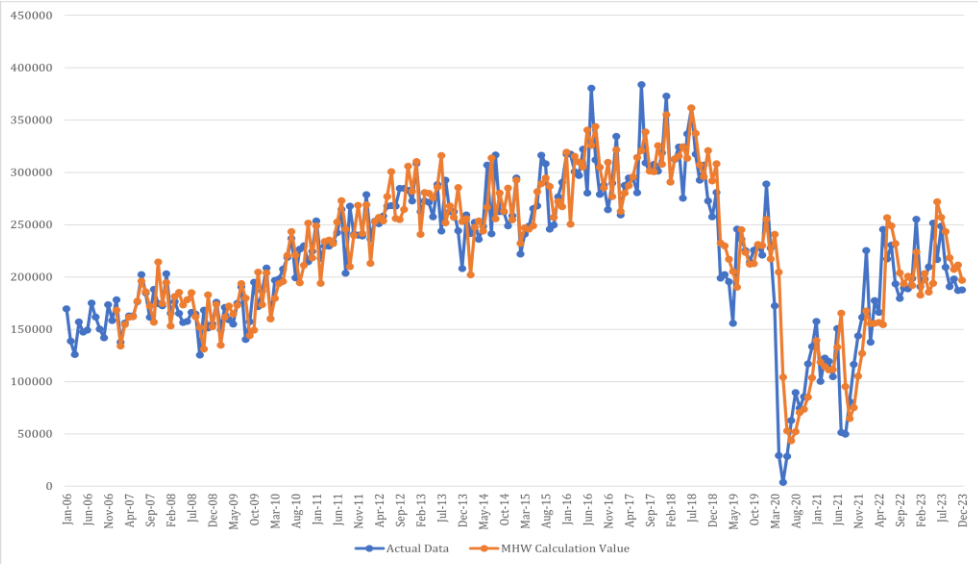

Figure 4. Comparison Plot of Actual Data and MHW Calculation

3.6. Best Model Selection

After obtaining the optimum calculation results of the two models, the best model selection was carried out by calculating the Mean Absolute Error (MAE) and Mean Square Error (MSE) values of the two models and comparing the smallest values **[13][14]**. The results of the MAE and MSE values are shown in **Table 4**.

Table 4. Results of MAE and MSE Values

Model	MAE	MSE
DES Damped Trend	23612.461	1061042411.507
Multiplicative Holt-Winters	21415.556	961525264.508

Based on **Table 4**, the Holt-Winters model has a smaller MAE and MSE value, 21415.556 and 961525264.508, compared to the model from Damped Trend Exponential Smoothing, which has an MAE value of 23612.461 and 1061042411.507. It shows that the Holt-Winters model can better forecast the number of domestic airplane passengers compared to the Damped Trend Exponential Smoothing model.

3.7. Forecasting Results

The next stage was forecasting the number of domestic airplane passengers at Kualanamu Airport using the best model for the next 12 periods. **Table 5** shows the results of forecasting the number of domestic airplane passengers at Kualanamu Airport for the next 12 periods using Holt-Winters Exponential Smoothing.

Table 5. Forecasting Results of Number of Airplane Passengers

Period	Forecasting
January 2024	220142.34
February 2024	165512.24
March 2024	179177.63
April 2024	167613.32
May 2024	164625.91
June 2024	191855.16
July 2024	207852.89
August 2024	199385.39

Period	Forecasting
September 2024	194575.69
October 2024	200386.60
November 2024	208763.37
December 2024	208716.45

Based on **Table 5**, the forecasting results for the number of domestic air passengers at Kualanamu Airport in 2024 are presented. The forecast shows that throughout 2024, the number of passengers is expected to fluctuate, with the highest number predicted in January at 220,142.34 passengers and the lowest in May at 164,625.91 passengers.

3.8. Accuracy of Forecasting Results

After obtaining the forecasting results, the last stage was to evaluate the results to determine the accuracy level of the MAPE value. The evaluation was done by comparing the actual data of the number of domestic airplane passengers at Kualanamu with the forecasting results for January-October 2024. **Table 6** presents the results of evaluating the MAPE value of forecasting the number of domestic airplane passengers at Kualanamu Airport with Holt-Winters Exponential Smoothing.

Table 6. Evaluation of Forecasting Value Results

Period	Actual Data	*Forecasting*	|DA-F|	MAPE
January 2024	225772	220142.345	5629.655	2.494%
February 2024	178374	165512.237	12861.763	7.211%
March 2024	158265	179177.633	20912.633	13.214%
April 2024	230344	167613.323	62730.677	27.233%
May 2024	191394	164625.908	26768.092	13.986%
June 2024	190287	191855.159	1568.159	0.824%
July 2024	216423	207852.886	8570.114	3.96%
August 2024	190270	199385.392	9115.392	4.791%
September 2024	205372	194575.695	10796.305	5.257%
October 2024	177282	200386.6	23104.6	13.033%
Total MAPE Value				9.2%

Based on **Table 6**, it can be seen that the forecasting results have a total MAPE value of 9.2%. In addition, it can also be seen that the difference in the value of the actual and forecasting data is directly proportional to the MAPE value in each period segment. It can be seen when the difference value experiences the largest deviation, namely in the April 2024 period, with a difference value of 62730,677. The MAPE value jumps high to 27.233%. Then, the difference value experienced its lowest deviation, namely in the June 2024 period, with a difference value of 1568,159. The MAPE value experienced its lowest condition of 0.0824%. The spike in the MAPE value in April 2024 is likely due to the tradition of mudik during the Eid al-Fitr celebration, which significantly increased the number of air passengers compared to previous forecasts. Based on these things, the forecasting results with Holt-Winters are relatively sufficient to describe the conditions that occur in the actual data. The MAPE value of 9.2% is based on **[21]** the criteria, which is very good with the MAPE range < 10%.

4. Conclusions

Several conclusions are obtained in this study based on the results and discussion.

1. The calculation of Damped Trend Exponential Smoothing with the Double Exponential Smoothing Damped Trend model with smoothing parameters was obtained, namely $\alpha = 0.56$; $\beta = 0.0001$; and $\phi = 0.98$ and an RMSE value of 32489.21. Then, the Holt-Winters calculation was also obtained with the Multiplicative model with smoothing parameters, namely $\alpha = 0.573, \beta = 0.000648$; and $\gamma = 0.143$ and an RMSE value of 31008.47 in predicting the number of domestic airplane passengers at Kualanamu Airport.
2. Holt-Winters Exponential Smoothing is much better at predicting the number of domestic airplane passengers at Kualanamu Airport than Damped Trend Exponential Smoothing because it has lower MAE and MSE values.
3. The results of forecasting the number of domestic airplane passengers at Kualanamu Airport with the best method, Holt-Winters Exponential Smoothing, have a MAPE value of 9.2% and a MAPE value criterion of "Very Good."

For the management of Kualanamu Airport, this article may serve as input and a proactive step in formulating policies related to the number of airlines, particularly for domestic flights, in connection with the volume of passenger departures. Furthermore, future research could explore other methods, such as the application of machine learning techniques.

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