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The Forecasting for Number of Airplane Passengers at International Airport Soekarno Hatta, Jakarta Using Some Time Series Models

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ABSTRACT: Indonesia is a vast country comprising five major islands that serve as the economic centers. Consequently, transportation methods, such as airplanes, are essential for facilitating economic transactions between these islands. The number of airline passengers is a crucial component in fostering the growth of the air transportation industry, which significantly influences the economy between islands. Therefore, it is essential to conduct periodic analyses of passenger numbers. A forecast analysis that predicts the number of airline passengers for the upcoming period will offer valuable insights, enabling the air transportation sector to continue its successful development. This research focuses on forecasting the monthly number of airplane passengers for the upcoming year at Soekarno-Hatta Airport, utilizing passenger data from January 2015 to August 2024. Four distinct time series models will be employed in this analysis: additive decomposition, multiplicative decomposition, Holt-Winters additive, and Holt-Winters multiplicative. The most critical aspect of evaluating the best model involves analyzing the smallest error results from each model, utilizing the Mean Absolute Error (MAE) testing tool for this purpose. The Holt-Winters additive model emerges as the superior choice, while both the decompose additive and decompose multiplicative models were unable to generate data with sufficiently narrow gaps, particularly during the significant decline in passenger numbers caused by the COVID-19 pandemic.

KEY WORDS: forecasting, time series, decompose additive, decompose multiplicative, Holt Winters additive, Holt Winters multiplicative

1. INTRODUCTION

Demand for air travel is primarily driven by business and leisure activities. Economic factors play a significant role in influencing this demand. This occurs because transportation is an essential need for society that cannot be separated; thus, the demand for transportation increases along with the growing population [1]. Downturns lead to a decrease in demand for both leisure and business travel, which, in turn, Economic downturns reduce the demand for air transport. Conversely, periods of economic growth increase it. Demand for leisure and business travel is driving an increase in the demand for air transportation. Indirectly, the number of airline passengers is closely linked to economic growth. Air transport enhances the growth of the local economy, contributes to the development of companies, and thereby increases the competitiveness of businesses [2]. Consequently, forecasting the number of passengers for the upcoming period is crucial, as it can offer insights into the future revenue that an airline company is likely to generate and in designing development strategies for air service providers. Several factors contribute to the complexity of time series forecasting. Including the sequence of input data and systematic patterns, such as Seasonality and stationarity, as well as the length of the prediction horizon. Among quantitative forecasting methods, random noise is a significant factor. Statistical approaches are particularly well-known for their application in these complex systems. Below, we briefly review these techniques in the relevant literature on air passenger demand forecasting. The basic regression analysis to consider causal relationships between air passenger demand and other variables. They analyzed big data from online search queries to determine which variables are reflected in short-term fluctuations of air passenger demand [3]. A forecasting approach using an Econometric Dynamic Model (EDM) to estimate passenger demand in the Mexican air transport industry. They applied the panel data Arellano-Bover method to calibrate the EDM, which was validated by the Sargan test and the Arellano-Bond Autocorrelation test [4]. City-pair air passenger demand at the route level model using a type of Discrete Choice Method (demand assignment). Discrete Choice Methods are widely used for the analysis of individual choice behavior. Holt-Winters and AutoRegressive Integrated Moving Average (ARIMA) models are two practical methods among statistical time series forecasting models [5]. The Holt-Winters method, which uses exponential smoothing, is an effective approach to forecasting seasonal time series [6]. A forecasting the number of air passengers in the UK using monthly air passenger data based on a smoothing method[7]. A modified version of the Holt Winters method[8] and Combination Holt Winters with Bootstrap aggregating (also called Bagging, a well-known machine learning technique) to improve the accuracy of air passenger forecasts[9]. The present research employs four methods to predict the number of air passengers at Soekarno-Hatta International Airport in Jakarta. These methods include Time Series Decompose Additive, Time Series Decompose Multiplicative, Holt-Winters Additive, and Holt-Winters Multiplicative. Among these four methods, the one with the smallest Mean Absolute Error (MAE) will be selected and recommended as the most suitable for forecasting the number of air passengers for the next 12 months. The concept of MAE was discussed [10]

2. DATA DESCRIPTION AND ANALYSIS

In this study, we analyze data on the number of airplane passengers at Soekarno-Hatta International Airport in Jakarta. The dataset spans the period from January 2015 to August 2024, as illustrated in Figure 1. Table 1 presents the descriptive statistics of the data. We obtained the data from the official website of Central Bureau of Statistics Indonesia (www.bps.go.id). which provides comprehensive information on airlines operating in both the domestic and international markets of Indonesia.

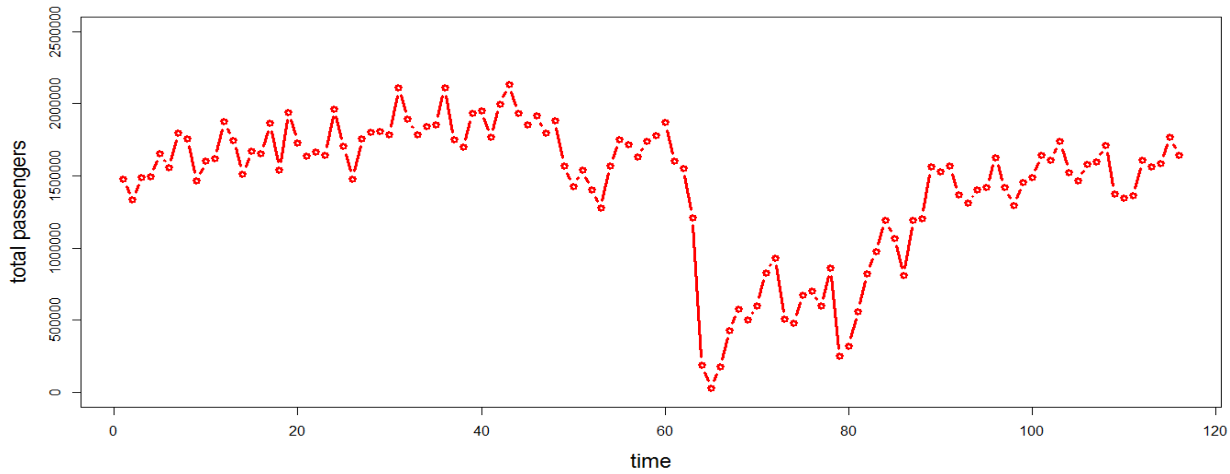

Figure 1. Plot of the Number of Airplane Passengers

Tabel 1. The Statistics Descriptive Airplane Passengers Data

N	mean	Standard deviasion	minimum	maximum
116	1439000	471711.4	27500	2132000

Based on Table 1 and Figure 1, it is evident that the number of airline passengers at Ahmad Yani Airport in Semarang exhibited fluctuations that generally increased from 2015 to 2024. However, between 2015 and 2019, there were fluctuations that tended to decrease, with variations in passenger numbers during specific seasons, such as holidays. The peak number of passengers occurred in 2018, reaching a total of 2,132,000, while the lowest number was recorded in 2020, with only 27,500 passengers. This decline in passenger numbers can be partly attributed to the impact of the COVID-19 pandemic, which affected both Indonesia and the global community.

3. METHODOLOGY

3.1 Time Series Decomposition

In general, the time series decomposition model consists of data patterns and errors. The data patterns are influenced by two key factors: trend and seasonality. The trend pattern will be analyzed over an extended period, during which a data pattern that either rises or falls will emerge, while seasonal pattern exists when a series is influenced by seasonal factors (e.g., the quarter of the year, the month, or day of the week). Seasonality is always of a fixed and known period. In general, there are two types of decomposition time series models: additive decomposition and multiplicative decomposition. Additive decomposition represents the sum of the trend, seasonal component, and error, while multiplicative decomposition represents the product of these three components. Mathematically, both models can be expressed as follows: $\hat{Y}_t = T_t + S_t + E_t$ dan $\hat{Y}_t = T_t \times S_t \times E_t$, respectively. Where $\hat{Y}$ it is the time series value (model data) at period t, S_t Is the seasonal component (or index) at period t, T_t Is the trend cycle component at period t, and E_t is the irregular (or reminder) component at period t.

3.2 Holt Winter Multiplicative

This model is based on four equations, each of which can be expressed as follows: that compute the average value of the sequence in the past (Level), the trend of evolution in the future (Trend) and a seasonal term (Seasonality, which allows to exploit the presence of repetitive patterns), finally the last equation computes the forecast [11], [12]. The four equations that form the foundation of the Holt-Winters multiplicative model can be defined mathematically as follows.

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

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

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

(4) $\hat{Y}_t = (L_t + b_t m)S_{t-s+m}$

3.3 Holt Winter Additive

The four equations that form the foundation of the Holt-Winters additive model can be defined mathematically as follows.

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

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

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

(4) $\hat{Y}_t = (L_t + b_t m) + S_{t-s+m}$

Here α, β, γ are the smoothing parameters (where α, β, γ lies in the interval [0, 1]), length of the seasonality is s,number of forecast ahead is m and observed data at time t is Y_t[13]. The best model selection could be estimated using error sizes, such as mean absolute errors (*MAE*). *MAE* (*Mean Absolute Error)* is the average deviation of the absolute value (actual) difference with a predicted (forecasting) value [14 – 16]. A forecasting model is considered highly accurate only if the model has the least error rate [17][18].

$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|Y_t - \hat{Y}_t\right|$

4. RESULT

The data on the number of airplane passengers at Soekarno-Hatta International Airport from January 2015 to August 2024 demonstrates an upward trend and exhibits non-stationarity. Furthermore, the data indicates the presence of seasonality, as illustrated in Figure 1. The fact is that four time series models decomposed additive, decomposed multiplicative, Holt-Winters additive, and Holt-Winters multiplicative can be utilized as a foundation for forecasting the number of airplane passengers over the next year. The parameters for the Holt-Winters additive and multiplicative models are presented in Table 2. These parameters have yielded resulting in a lower Mean Absolute Error (MAE) value compared to both the additive and multiplicative decomposition models. Therefore, both the Holt-Winters additive and Holt-Winters multiplicative methods demonstrated low mean absolute error (MAE) and can be utilized for future predictions. However, the model employing the holtwinter additive method, exhibited the best overall performance when all estimates were compared to the actual data, has a smaller error value compared to other models.

Table 2. The smoothing parameters of time series models

Model	α	β	γ	MAE
Holt Winter Additive	0.8376623	0	1	138110.9
Holt Winter Multiplicative	0.8569904	0	0.179955	146947.7
Decompose Additive	-	-	-	354428.6
Decompose Multiplicative	-	-	-	366989.6

Figure 2 is also presented to provide a precise comparison of the Mean Absolute Error (MAE) values for each model utilized. Table 2 indicates that the MAE of the Holt-Winters additive model (represented by the red bar) is lower than that of the other models.

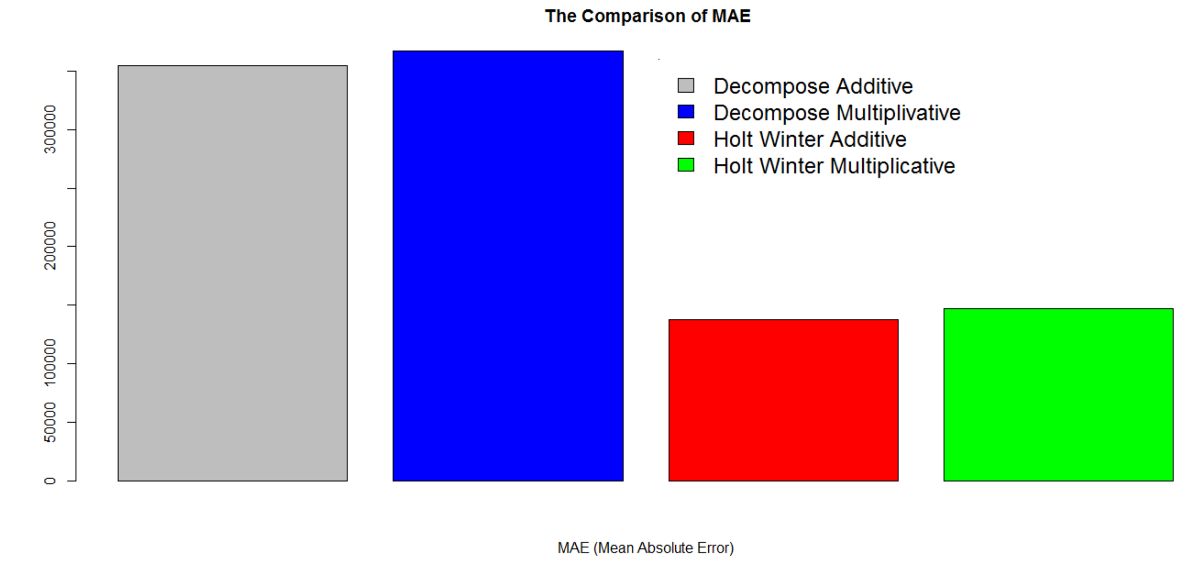

Figure 2. Comparison of MAE Value for The Models

The comparison between actual data (observation) and the data generated by the additive and multiplicative decomposition models is illustrated in Figure 3. Both decomposition models struggle to produce accurate data when there is a significant gap, particularly due to the drastic decline in the number of airplane passengers during the COVID-19 pandemic.

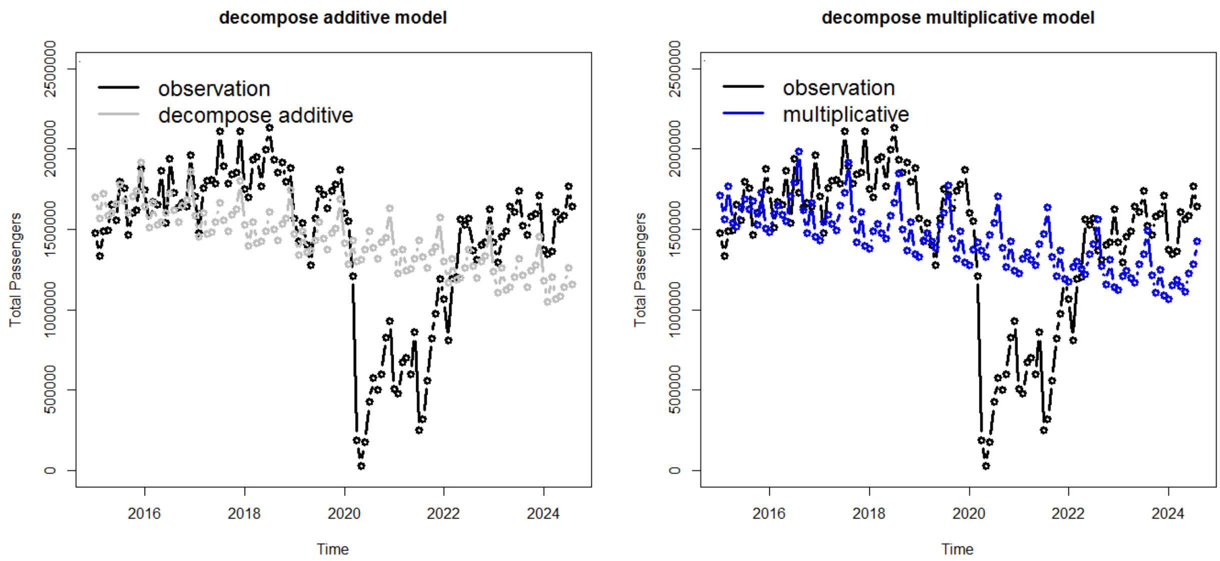

Figure 3. Comparison of Actual Data and Predicted Data from the Decompose Additive and Multiplicative Model

The opposite is demonstrated by the capability of the Holt-Winters additive and Holt-Winters multiplicative models to generate data that closely resembles actual data. Both models are proficient in producing high-quality data that is nearly identical to real-world data, despite the significant gap in the number of airplane passengers caused by the Covid-19 pandemic. These results are illustrated in Figure 4.

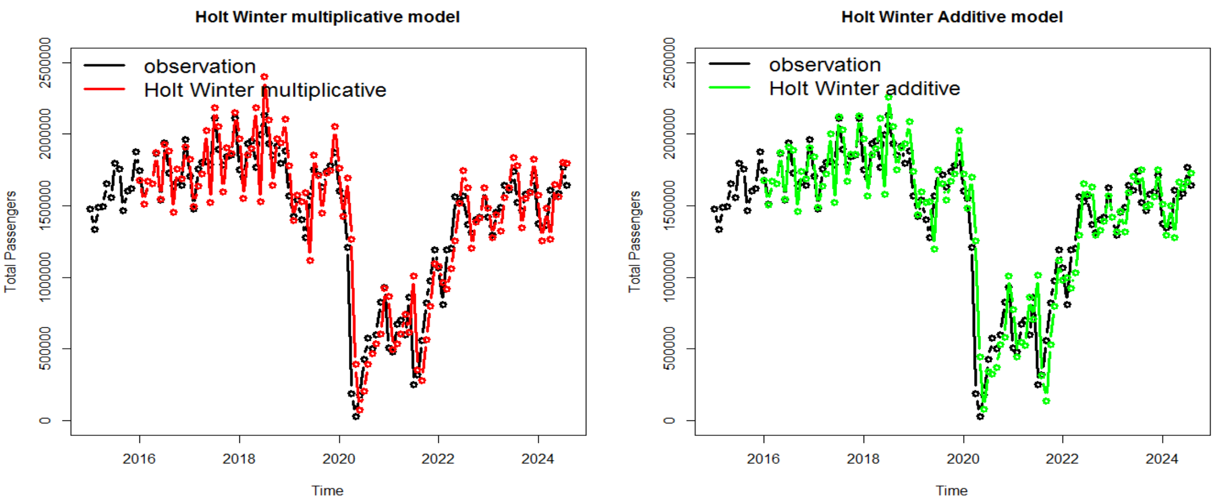

Figure 4. Comparison of Actual Data and Predicted Data from the Holt Winters Additive and Multiplicative Model

Based on the data presented in Figure 4, the Holt-Winters model will be employed to forecast the number of aircraft passengers at Soekarno-Hatta Airport for the upcoming year. The results of this forecast are illustrated in Figure 5, which indicates an upward trend in the number of aircraft passengers.

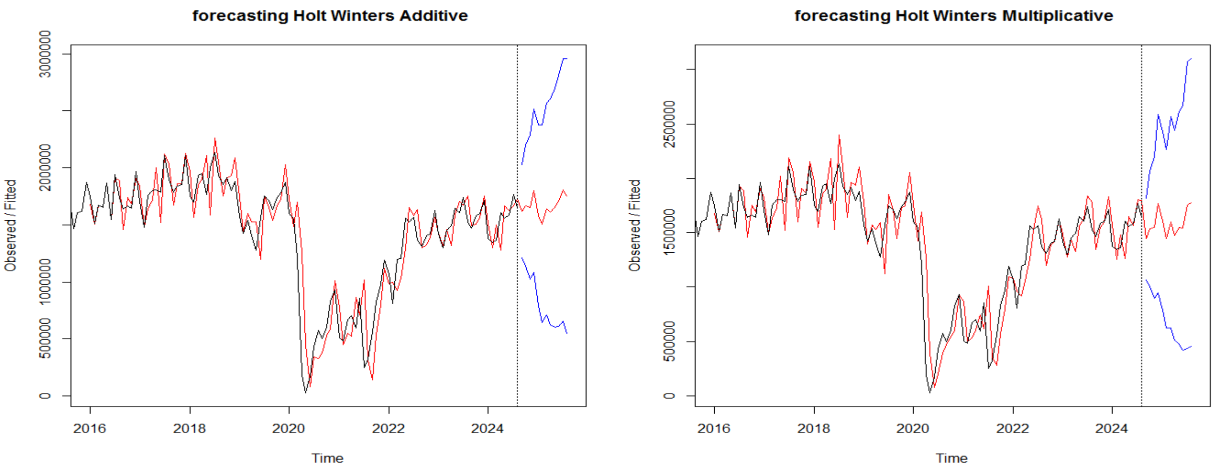

Figure 5. Comparison of The forecasting for a 12 month by Holt Winter Addititve and Multiplicative Models

5. CONCLUSION

The study focused to make a tool available for International Airport Soekarno Hatta to analyze the number of air passengers during January 2015 to August 2024. Two models Decompose, and Holt-Winters model have been fitted to the data. Both Holt Winter models have shown satisfactory results. But by using diagnostic check on these two models proved that Holt-Winters' Additive model is best for this data. Hence forecast have been computed by using Holt-Winters' Additive model. Even from fore studies it has proven that Holt-Winters' Additive model is best fit for many data concern with traffic, tourist and number of passengers. Therefore, Holt-Winters' Additive model can be used as a tool to forecast number of passengers for a month This kind of analysis is very useful for forecasting the Air traffic.

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