Forecasting Airline Passenger Demand for the Long-haul Route: The Case of Garuda Indonesia

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Abstract: This paper discusses the forecasting of passenger demand for the long-haul route at Garuda Indonesia, which is the legacy air carrier of Indonesia. We focus on routes with the largest share, namely China and Saudi Arabia. We use two forecasting models for this purpose. First is a regression model with the population in each country as the independent variable, and second is the Winter's model that is suitable for data with trend and seasonality characteristics, such as airline passenger. The performance of both methods is analysed using forecast errors, which are a mean squared error (MSE), mean absolute deviation (MAD), mean absolute percentage error (MAPE) and Tracking Signal. The results show that Winter's model is more suitable for the China route, while the regression model is more suitable for Saudi Arabia route. The forecasting results for 2019-2028 show a significant growth of passengers for both routes that must be anticipated by the company.

1 INTRODUCTION

The airline's industry normally deals with massive risks, from the rise and fall in jet fuel price and currency exchange rates, to enormous capital expenditures, rivalry from low cost carrier and instability in passenger demand (Pyke et al., 2018). The industry is a significantly highly-regulated industryto be based, it is vital for the decision maker and policy planner to observe and assess the airline's performance by utilizing productivity analysis and efficiency (Chen et al., 2018).

The aviation authority of every nation distributes factual indicators each year, for example, cargo and passenger turnover volume, which demand for improvement of the nation's aviation industry (Xu et al. 2019). Accurate forecasting of these indicators is important for both airlines and airports, to oversee and build their capability, increment passenger load rate, decrease operation costs, enhance service quality, reduce environmental impact affect and enhance their competitive advantage (Xu et al., 2019). Demand forecasting enables administrators to make master plans on investment, management and construction (Flyvbjerg et al., 2005). For this purpose, selecting a forecasting model that is suitable for the aviation business is a valuable task and crucial (Xie et al., 2014).

Based on Airbus (2013) and Boeing (2013) data, the aviation industry will experience growth of passenger demand at the rate of almost 5% annually for the next 20 years.

The airlines carriers adjust their capacity to deal with the passenger growth, by either increasing the aircraft size or frequency, which may prompt distinctive quantities of aircraft movements, but the movement of the aircraft, which is the number of operated flights on one leg, affects the different parts of the air transport system (Kolker 2016). For instance, Kolker (2016) describes that one trip with a wide-body aircraft may prompt less emission and less immersion of airplane terminals and air space than two flights with narrow body aircraft that carrying together a similar number of passengers. For this reason, Kolker (2016) also explains that forecasting aircraft movements are essential for assessing future developments and technologies of the air transportation framework system.

Other researcher, such as Gelhausen (2018), also explains that long-term planning of transportation system requires to know future transport prerequisites for various financial scenarios.

The objective of this study is to select a forecast model that is suitable to predict the number of an flights flying Garuda Indonesia airlines that can be used as a reference for various strategic and

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operational decision making, such as selecting the number of aircraft for certain types of aircraft needed in the future (or fleet planning). We focus on long-haul routes with highest revenue share, namely, China and Saudi Arabia. China is chosen because the growth of Chinese travellers to Indonesia is the largest in recent years (The Jakarta Post, 2018), while Saudi Arabia is selected because the country is the popular pilgrimage destination for Indonesian Moslem residents (Susanty, 2017). According to the data from The Ministry of Religious Affairs (MRA), there is a 63.6% increase in pilgrimage to 818,000 in 2016 from just 500,000 in 2012 (Susanty, 2017).

It is expected that this study will provide better understanding related to the implementation of forecasting decisions related to the operation planning that is very important in the aviation industry. Specifically, this study gives insights on the reality of airline passengers in Indonesia, especially for the long haul. It can be used as a reference for Garuda Indonesia to choose the right operational decision to maximize its profitability and customer service level.

The paper is structured as follows. A relevant literature review is presented in Section 2, relevant literature review in Section 3, findings and discussion in Section 4, and conclusion and recommendation in Section 5.

2 LITERATURE REVIEW

Forecasting is very important in demand management, because forecasting provides an estimation of future demand which is the basis of many business decisions (Wiesner et al., 2019). Forecasting methods are basically can be classified into quantitative and qualitative methods (Wisner et el., 2018; Heizer et al., 2017). Qualitative techniques are used when the available data is very limited, or even irrelevant, for this reason a qualitative technique is needed to be based on intuition or judgment from an expert in their field, while quantitative techniques use mathematical methods that utilize historical data and can also include a number of relevant variables (Wiesner et al., 2019).

According to Heizer et al. (2017), the quantitative approaches are basically can be classified into time-series models (such as moving average and exponential smoothing models, which forecast only based on past data) and associative models (such as regression model, that use changes in one or more variables to predict the changes in dependent variables). Concerning, the the time series models, they usually have the following components: trend variations (persistent upward and downward pattern), cyclical variations (repeating up and down movements that are more than one year and influenced by external factors such as political or macroeconomic factors), seasonal variations (regular up and down fluctuations, such as monthly or yearly), and random variations (erratic, unsystematic fluctuations due to random variations or unforeseen events) (Heizer et al., 2017).

Regarding airline passenger demand forecasting, Carreira et al. (2017) forecast passenger demand of TAP Portugal airline, the legacy airlines of Portugal, to predict the demand in several cities in Brazil. They use a regression model by looking at the relationship between the passenger demand, the city's population, and whether there is a direct flight to the destination. Kolker et al. (2016), on the other hand, implement the forecast of aircraft movement (FoAM) method, which basically divides each flight segment into a quantity of passengers, distance and aircraft type category, and then predicts the passenger growth rate each year as the input parameter from the data obtained from airbus (2013). The FoAM model is done using Java and the forecast process is done automatically.

Hsu et al. (2011), on the other hand, conduct forecasting on demand that is very fluctuating using Grey topological and Markov-chain models carried out on EVA air in Taiwan by considering several different economic conditions.

Lastly, Xu et al. (2019) use a mixture of autoregressive, integration, moving average, seasonal autoregressive, seasonal integration, and seasonal moving average (SARIMA) and support vector regression (SVR). In their research, Xu et al. (2019) include the white gaussian noise in the forecast model and the proposed procedure are as follows. First, time series data is used in SARIMA models to get the parameters. Second, the SARIMA results are obtained based on the parameters specified. Third, the white noise gaussian is recalculated based on the results of SARIMA. Fourth, four variable combinations are combined to be processed into a mixed model to predict statistical indicators in the airline's industry. Finally, the results of the forecast can be obtained.

As can be seen, there are different forecasting models that are used to predict airline passenger demand, however the models are a bit complex and may not be practical to be used in the real world. Therefore, in this study, we choose to compare two forecasting models that are practical and can be used to forecast Garuda Indonesia's airline passengers.

3 RESEARCH METHOD

3.1 Research Stages and Data Collection

The purpose of this study is to predict Garuda Indonesia passenger demand for long-haute routes, focusing on Saudi and Chinese routes, which will be valuable for several strategic decisions, such as fleet planning.

We use two forecasting models that are suitable for predicting airline passenger demand, namely the regression model by Carreira et al. (2017), and the classic Winter's model that takes into account trend and seasonality aspects (Chopra and Meindl, 2016). In order to determine the suitable forecast method, we use compare passenger demand data and the forecast results for the period of 2013-2018. Concerning Winter's model, we use MS Excel Solver to find the optimal values of the smoothing constants. The suitability of the models is then determined by analysing their performances using the forecast errors (MAD, MSE, MAPE, and tracking signals). Based on the results, we then forecast the demand for 2019-2028 using the forecast method with the least errors.

Data for this study are collected through internal demand passenger data from the Market Research Department in Garuda Indonesia. The data is obtained from the Global Distribution system (GDS) for bi-direction passenger traffic from all cities with the origin of all cities in Indonesia and all cities in China and Saudi Arabia, including transit passengers specifically for Garuda Indonesia passengers. The population data of China and Saudi Arabia are retrieved from http://www.worldometers.info, which is owned by DADAX, that is run independently by an international team of volunteers, researchers and developers (Worldometers, 2019).

3.2 Forecasting Models

As previously mentioned, the first model is adjusted from Carreira et al. (2017), which formulate a regression model using comparative demand data and population data. The advantage of using this method is to utilize the size effects of the Chinese and Saudi Arabian populations on demand from Garuda Indonesia. The regression equation is formulated as the following:

$$\ln D = a + b.\ \ln P + \qquad (1)$$

Then, the future demand equation is:

$$D = e^{(a+\ )} P^{b} \qquad (2)$$

Where D is airline passenger demand, P is the country's population, a and b are regression coefficients, and ε is the error term.

The second model that we use is Winter's model. Chopra and Meindl (2016) explain that Winter's model is suitable when the systematic factor of demand has a trend, a level, and a seasonal factor. The formulation is just like in Formulation (3).

Systematic Component of Demand = (Trend + Level) x Seasonal Component (3)

The forecast equation, on the other hand is presented in Formulation (4), while the trend equation is explained in Formulation (5), level equation is presented in Formulation (6), and the seasonal factor equation is described in Formulation (7).

$$F_{t+1} = (L_t+T_t)S_{t+1} \text{ and } F_{t+l} = (L_t + lT_t)S_{t+l} \qquad (4)$$

$$T_{t+1} = \ (L_{t+1} - L_t) + (1-\ )T_t \qquad (5)$$

$$L_{t+1} = \ (D_{t+1} / S_{t+1}) + (1-\ )(L_t + T_t) \qquad (6)$$

$$S_{t+p+1} = \ (D_{t+1} / L_{t+1}) + (1-\ )S_{t+1} \qquad (7)$$

Where:

F_t forecast at time t
L_t level at time t
T_t trend at the time t
S_t seasonal component at the time t
α α is the weight for the level
β weight for the trend
δ weight for the seasonal component
P seasonal period
l time step ahead to forecast

The value for the (the level's smoothing constant) is 0 < < 1. The value for the (trend's smoothing constant) is 0 < < 1, while the value for the (is (the seasonal factor's smoothing constant) is 0 < < 1). Using this method, we need at least one-year actual data to forecast future demand.

3.3 Measures of Forecast Errors

In this study the forecast error analysis is carried out by using several commonly used methods, which are MSE, MAD, MAPE and Tracking Signal.

Mean Squared Error (MSE) is one of the forecast error analysis methods that compare whether errors generated by one forecast method are greater than other forecast methods that are more accurate. MSE is related to the of the forecast errors. MSE equation is in Formulation (8), where Et is the error (the difference between forecast and actual values) at period *t.*

$$MSE_n = \frac{1}{n}\sum_{t=1}^{n} E_t^2 \tag{8}$$

Mean Absolute Deviation (MAD) is used in estimating the standard deviation from random components when the assumed random component is normally distributed. MAD is better at measuring errors than MSE when the cost of forecast error in forecasting technique is proportional to the number of errors. The MAD equation is in Formulation (9), and is the sum of the absolute deviation A_t (Formulation 10).

$$MAD_n = \frac{1}{n}\sum_{t=1}^{n} A_t \tag{9}$$

$$A_t = |E_t| \tag{10}$$

MAPE, on the other hand, is the average of the absolute error in terms of percentage. MAPE is a very good measure in measuring forecast error when the calculated forecast has significant seasonality and demand related between one period to another. MAPE equation is in Formulation (11), where E_t and D_t are error and demand in period *t* respectively.

$$MAPE_n = \frac{\sum_{t=1}^{n}\left|\frac{E_t}{D_t}\right|100}{n} \tag{11}$$

The last measure that we use is tracking signal (TS), which is the ratio of bias to MAD. When TS in a period is outside the ±6 value, it is a sign that the forecast is biased. The tracking signal equation can be seen in Formulation (12), and the bias value is explained in Formulation (11).

$$bias_n = \sum_{t=1}^{n} E_t \tag{11}$$

$$TS_t = \frac{bias_t}{MAD_t} \tag{12}$$

4 FINDINGS & DISCUSSIONS

4.1 Adjusted Carreira et al. (2017) Model

The results of applying the adjusted regression model by Carreira et al. (2017) to forecast Garuda Indonesia's passenger demand to China and Saudi Arabia can be seen in Tables 1 and 2.

It can be seen that for China route that the adjusted R square value is 0.815, with the t-value of 4.2, and the p-value is less than 0.005. For the Saudi Arabia route, we can see that the adjusted R square value which is 0.815, with t- value 4.20 and the p-value is less than 0.005. Thus, we can say that the model can be used to forecast the passenger demand to both routes.

Table 1: Regression result for China.

R Square	0.81554618		
Adjusted R Square	0.76943272		
Standard Error	0.16868676		
	Coefficients	*t Stat*	*P-value*
Intercept	-741.017503	-4.1327289	0.01446176
X Variable 1	35.8061659	4.2054303	0.01363614

Table 2: Regression result for Saudi Arabia.

R Square	0.81544393		
Adjusted R Square	0.76930491		
Standard Error	0.10966107		
	Coefficients	*t Stat*	*P-value*
Intercept	-67.7377908	-3.5319395	0.02418827
X Variable 1	4.66742158	4.2040016	0.01365181

Applying the model, the comparisons between actual and forecasted passenger demand can be seen in Figures 1 and 2. The results show that the forecasts look relatively China and Saudi Arabia routes, using both forecasting models.

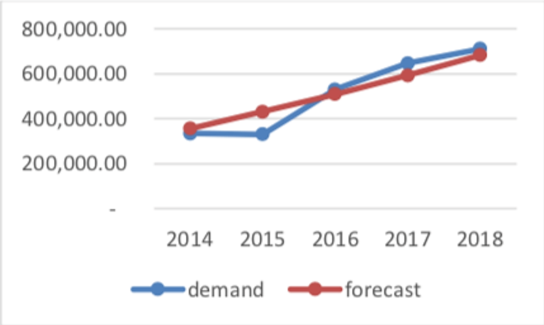

Figure 1: Actual and forecast (regression model) for China.

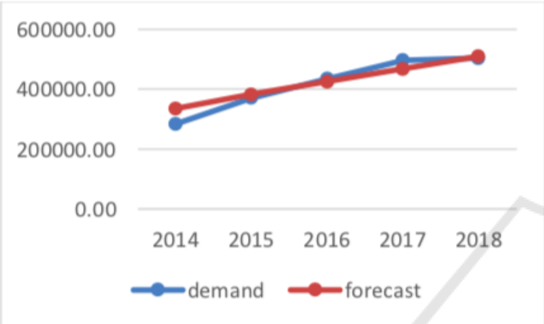

Figure 2: Actual and forecast (regression model) for Saudi Arabia.

4.2 Winter's Model

As previously mentioned, in applying Winter's model to forecast the passenger demand to China and Saudi Arabia routes, we use optimal values of smoothing constants generated by MS Excel Solver, and the optimal values for the smoothing constants can be seen in Tables 3 and 4.

Table 3: Smoothing constants for China's route.

China winter's model	
alpha	0.6062
Beta	0.9900
Gamma	0.9900

Table 4: Smoothing constants for Saudi Arabia route.

Saudi winter's model	
alpha	0.4762
Beta	0.2470
Gamma	0.9999

The smoothing constants values are then used in Winter's model formulations, and the actual and forecast values for both routes are presented in Figures 3 and 4.

The forecast results of Chinese routes (Figure 3) look very close to the actual demand, even better than the results of the to route the previous regression model (Figure 1). However, this is contrary to the forecast results of Saudi Arabia (Figure 4). It can be seen that the differences between actual and forecast in 2014 and 2016 are significant, although the differences are not that significant in the other years. Thus, it seems that the forecast using adjusted Carreira et al. (2017) model looks better for the Saudi Arabia route than Winter's model.

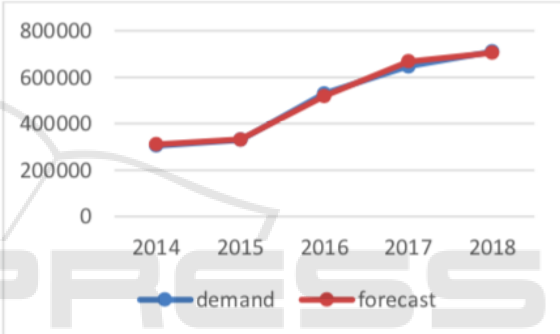

Figure 3: Actual and forecast (Winter's model) for China.

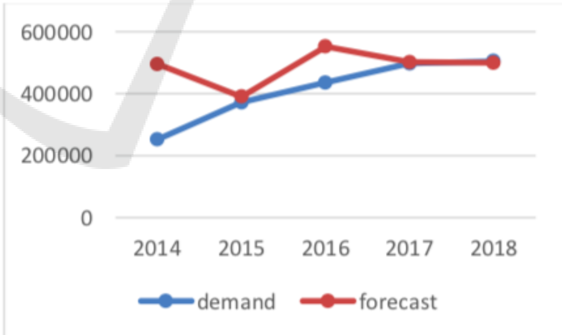

Figure 4: Actual and forecast (Winter's model) for Saudi Arabia.

4.3 Forecast Errors

The forecast errors of both models on both routes are calculated, and presented in Table 5.

For the Chinese route, the MAD, MSE, and MAPE values of Winter's model look much smaller than the regression model, ±while tracking signal for both models is still within 6, with tracking signal. value of the regression model is closer to zero than that of Winter's model.

Contrary to the results for China route, the results for Saudi Arabia route show that the MAD, MSE, and MAPE values of the regression model are much smaller than those of Winter's model, with tracking the signal of regression model close to zero.

The difference in the results of China and Saudi Arabia routes may be due to the fact that the Chinese route has a seasonal pattern in each year compared to the Saudi Arabia route, which seasonal pattern cannot be well described because the Hajj season and the Ramadan season move in advance approximately 10 days each year.

Table 5: Forecast errors.

CHINA ASSOCIATIVE REGRESSION MODEL			
TS	MAD	MSE	MAPE
(0.49)	44,801	2,954,183,230	10.6%
CHINA TIME SERIES WINTER'S MODEL			
TS	MAD	MSE	MAPE
(1.40)	21,378	744,040,486	6.0%
SAUDI ASSOCIATIVE REGRESSION MODEL			
TS	MAD	MSE	MAPE
(1.35)	9,276	136,243,278	1.8%
SAUDI ARABIA TIME SERIES WINTER'S MODEL			
TS	MAD	MSE	MAPE
(4.87)	77,525	14,603,142,791	26.0%

4.4 Forecasting Future Demand

Based on the results explained in the previous subsections, we forecast demand for Garuda's airline passengers for the next 10 years (2019-2028). Demand for China route is predicted using the Winter's model forecast method (see Figure 5), while the demand for Saudi Arabia route is carried out by the regression model (see Figure 6). The line in Figures 5 and 6 indicate the growth rate of airline passengers for both routes.

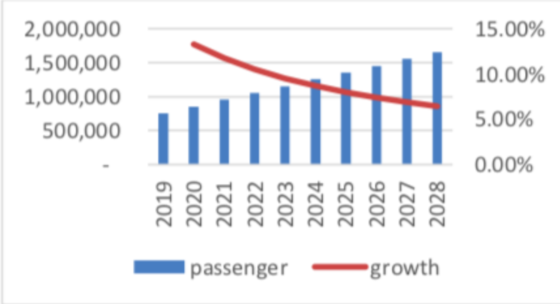

Figure 5: Forecast (Winter's model) for China.

The forecast results for the China route for the next 10 years show an annual average growth of almost 9 percent with a predicted 750.000 passengers in 2019 and reach more than 1.6 million passengers in 2028, while for Saudi Arabia the route shows the average growth of 6 percent each year with a prediction of about 550.000 passengers in 2019 and reaching more than 900.000 in 2028. The growth for the China and Saudi Arabia routes shows a higher number than Airbus (2013) and Boeing (2013) predictions, while they expect only almost 5 percent growth in passengers for Next 20 years.

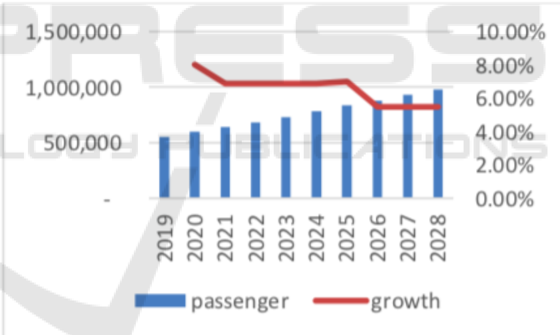

Figure 6: Forecast (Regression model) for Saudi Arabia.

To address the results of this forecast, it is highly recommended that Garuda Indonesia increase its seat capacity for flights to China and Saudi Arabia. This can by increasing the frequency of flights to China and Saudi Arabia, as well as opening routes directly from secondary cities in Indonesia to China or Saudi Arabia, and vice versa. The increase in the number of seats also needs to be supported by good fleet planning, which is the planning of the number of aircraft that can meet the demands for both routes, which must also be balanced with the company's financial capability.

5 CONCLUSIONS

The paper presents the forecasting analysis of airline passenger demand for the long-haul routes at Garuda Indonesia, the legacy airline of Indonesia. We compare two forecasting methods, which are suitable for the purpose, namely an adjusted regression model from Carreira et al. (2017) and Winter's model with optimal smoothing constants.

The results show that the regression model is more suitable for Saudi Arabia route, while Winter's model is more suitable for China route as indicated by the forecast error values.

The results may be due to the fact that China demand shows a seasonal pattern in each year, while for Saudi Arabia route, the passenger demand is mainly depending on the Hajj season and Ramadan season which are moving forward in approximately 10 days every year.

Forecast results for 2019-2028 show that the demand for Saudi Arabia and China grow at the rate of 6% and 9% and reach 900.000 and 1.6 million passengers in 2028 respectively. The results imply that Garuda Indonesia must anticipate the growth by increasing the seating capacity by increasing the flight frequency and/or using larger aircraft.

This study has limitations. Even though demand data from Garuda Indonesia is monthly data, however, the population data in annual data, thus, forecasting is conducted using annual data, that may not accurately reflect the actual situation.

Future research may include using the resulting forecast for strategic fleet planning, to maximize the profitability of the airline.

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