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Original Article

Modeling of domestic air passenger demand in The Papua Islands

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Abstract

Indonesia is an archipelagic country with diverse regions**.** Among them are several regions that are difficult to reach by land or sea transportation, such as Papua and West Papua in the Papua Islands. In the context of national transportation, such regions are referred to as regions with geographical constraints. This study aimed to predict both generation and attraction of air passengers in The Papua Islands. The study indicated that out of the fourteen independent variables as candidate predictors, only two significantly influenced generation and attraction: population and per capita GRDP. Over the next five years, it is predicted that generation and attraction will grow by 11.94% and 9.35% in Papua; and by 81.95% and 70.85% in West Papua. Over the next ten years, generation and attraction are predicted to grow by 26.03% and 29.14% in Papua; and by 94.79% and 96.26% in West Papua.

Keywords: Papua Islands, domestic air passengers, demand modeling, generation, attraction

1. Introduction

Indonesia is an archipelagic country with about 17,500 islands (Bradt, Drummond, & Richman, 2001), and the areal ratio between land and sea is approximately 30: 70 (Wang, Yim, Lee, Liu, & Ha, 2014) as shown in Figure 1**.** The geography is also dominated by hills/mountains, of which 127 are active mountains (Haryono, 2012). These conditions greatly affect the development of transportation in Indonesia. Several regions are difficult to reach by land or sea transportation modes, such as Papua Province and West Papua Province.

Papua Province and West Papua Province are categorized as regions with geographical limitations in Indonesia, in the Indonesian National Transportation Level. This is due to these regions being geographically dominated by steep slopes, at altitudes from 500 to over 3,000 meters above sea level, and with deep valleys. This region does not have one single railroad line, nor an A level terminal for land transportation. In this regard the developmental gap to urban areas in Indonesia is dramatic, as for example Jakarta has land transportation growing rapidly (Munawar, Irawan, & Fitrada, 2017). Currently air transportation still serves as the backbone of transportation in this region, especially in the Central Highland, and land transportation infrastructure remains inadequate. For internal travel people use air transportation, while for external they use sea transportation (Juniati, 2017). Moreover, the results of a research study conducted by Oktaviana, Sulistio and Wicaksono (2011) state that accessibility in this region is very poor, referring to index numbers IA-7.08 to IA-5.24.

During the last ten years, the air passenger demand in this region grew by 20.7% annually, while the growth of air passenger demand in Indonesia overall grew by 15.5% annually (Direktorat Jenderal Perhubungan Udara, 2016). IATA (2016) even predicted that the highest growth in the number of air passengers for the next decade will occur in Asia, including Indonesia. According to IATA, Indonesia will become the world's sixth largest airline travel market by 2034**.** Based on this assessment and considering that air transportation is a

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Figure 1. Map of Indonesia

vital transportation mode in this region, airport development as backbone of air transportation is a priority that must be dealt with early (Hossain & Alam, 2017; Saldiraner, 2013).

Making decisions and formulating policies for airport development in Indonesia cannot be separated from estimating air passenger demand in the timespan of the plan. According to Halpern and Graham (2016), air passenger demand is the most positive factor affecting the development of routes in the world. Therefore, estimating air passenger demand is the first step that must be performed at this time.

2. Literature Review and Methods

2.1 Literature review

Initially, the estimation of air passenger demand was carried out without taking into account the influences of independent variables, i.e. only using air passenger data in the past. This research was conducted by: Blinova (2007); Chen and Chen (2011); Defiani (2012); Samagaio and Wolters (2010); Song and Li (2008); Tsui, Balli, Gilbey, and Gow (2014); and Xiao, Liu, Hu, Wang, Lai, and Wang (2014). Over time, it was realized that there were several factors that influenced air passenger demand, and forecasts were made including these predictors. Such research was conducted by Barua and Mohapatra (2014); Carson, Cenesizoglu, and Parker (2011); Chudy and Pisula (2017); Gelhausen and Berster (2017); Mubarak (2014); Profillidis (2012); Scarpel (2013); Sohag and Rokonuzzaman (2016); and Srisaeng, Baxter, and Wild (2015). The variables used are socio-econometric factors, such as population, regional income (GDP), per capita income (GDP per capita), and consumer price index (CPI). In addition to socio-econometric factors, there are also studies that take into account geographical factors such as distance and travel time between airports. Such studies were conducted by Sivrikaya and Tunc (2013) at one of the airports in Turkey, by Cohen (2016) at Schiphol Airport in Amsterdam, by Nommik and Kukemelk (2016) at several airports in London, as well as by dan Terekhov, Ghosh, and Gollnick (2015), Khadaroo and Seetanah (2008) and Li & Trani (2014).

2.2 Methods

This study considered the influences of fourteen independent candidate variables, namely population (X_1), density (X_2), per capita GRDP (X_3), tourists (X_4), airlines (X_5), number of airports in one province (X_6), flight frequencies (X_7), imports (X_8), exports (X_9), universities (X_{10}), regional tourist destination (X_{11}), hospitals (X_{12}), large/medium companies (X_{13}), and workers (X_{14}). Data included the number of air passengers from 2012 to 2017, of which the study focused on Papua Islands, namely Papua Province and West Papua Province.

The research phase commenced with classical assumption tests, including normality test, homoscedasticity test, multicollinearity test, and autocorrelation test. The normality test was performed using a Shapiro-Wilk test because the data had <50 records. The homoscedasticity was tested using the Gletjer-test, and the multicollinearity was tested using tolerance values and VIF, and the autocorrelation test was performed using the Durbin-Watson method. The independent variables that passed the classical assumptions would then be checked for their correlations with the dependent variables using linear models, power models, exponential models, and logistic models. The model that showed the highest R^2 value was then used for the next regression test, until the equation model was obtained.

In order to predict the values of the independent variables in the years planned, the following growth formula was used:

$$P_n = P_o + (1 + r)^n$$

Description:

P_n = independent variable of the year of the plan
P_o = independent variable of the initial year
r = average annual growth rate
n = year of the plan

3. Results

3.1 Classical assumption tests

The classical assumption tests included a normality test, homoscedasticity test, multicollinearity test, and autocorrelation test. The normality test was performed to see whether the residuals from regression fit were normally distributed or not. In this study, the normality test was performed using the Shapiro-Wilk method because the number of samples was <50. The value of Shapiro-Wilk for Y_1 = generation was 0.97; and for Y_2 = attraction was 0.86 (Table 1). These exceed the required value (for $p > 0.05$) so it could be concluded that the data were normally distributed.

Homoscedasticity test was conducted to see whether a group (data category) has the same variance among group members. If the variance was the same, and this should be the case, the data are homoscedastic. Meanwhile, if the variance were not the same, the data would be heteroscedastic. The homoscedasticity test in this study was performed using the Gletjer-test, with threshold for $p > 0.05$. For Y_1 = generation, out of the fourteen independent variables tested there were three variables that were automatically removed from the system because they did not fulfill requirements, namely X_1, X_4 and X_{12}. For Y_2 = attraction, out of the fourteen independent variables tested there were two variables that were automatically removed from the system, namely X_2 and X_{12}.

The multicollinearity test was conducted to see whether there was a linear correlation between the independent variables, which later could cause bias or error in the model. The presence or absence of multicollinearity was tested based on the tolerance value and VIF on each variable in the model, where the permitted tolerance value was > 0.1 and VIF value was <10. From the test results, almost all variables did not meet the requirements. Therefore, the testing was conducted repeatedly by removing variables that had the highest VIF and the lowest tolerance at every round, until the remaining variables had tolerances and VIFs that were acceptable. From this process, the only variables that met the multicollinearity test were X_1 and X_3, with tolerance and VIF values of 0.361 and 2.769 respectively; both for Y_1 = generation and for Y_2 = attraction.

The last assumption test was autocorrelation test. This test aimed to see whether there was a linear correlation between errors in period t and period t-1 (before). In this study, the autocorrelation test was performed using the Durbin-Watson method, where the required autocorrelation value was between -2 and +2. If the DW value was below -2, it indicated positive autocorrelation, while a DW above +2 indicated negative autocorrelation. For this study, the Durbin-Watson value was 1.684 for Y_1 = generation and 1.961 for Y_2 = attraction.

Of the fourteen independent candidate predictors, only two significantly met the four assumption tests (normality, homoscedasticity, multicollinearity, autocorrelation). The variables in question were X_1 dan X_3, namely population and per capita GRDP.

3.2 Parameter estimation

Before the regression test was done, the closest regression model was first checked, based on the coefficient of determination R^2. The comparable models included linear regression model, rank regression model, exponential regression model, and logistic regression model. The results showed that among the models predicting X_1 or X_3, the highest R^2 value was in both cases for the linear regression model (Table 2). Therefore, linear regression was used in the next calculations.

3.3 Regression test

The results of the regression test are shown in Table 3, summarizing the results of regression fitting. The adjusted

Table 1. Classic assumption test results.

No.	Assumption test	Method	Requirements	Results	
				O_i	D_d
1	Normality	Saphiro –Wilk	Sign > 0.05	0.97	0.859
2	Homoscedasticity	Gletjer test	Sign > 0.05	X_1 = 0.545 X_2 = - X_3 = 0.894 X_4 = - X_5 = 0.531 X_6 = 0.694 X_7 = 0.539 X_8 = 0.694 X_9 = 0.937 X_{10} = 0.870 X_{11} = 0.875 X_{12} = - X_{13} = 0.722 X_{14} = 0.581	X_1 = 0.784 X_2 = - X_3 = 0.878 X_4 = 0.661 X_5 = 0.585 X_6 = 0.962 X_7 = 0.953 X_8 = 0.825 X_9 = 0.868 X_{10} = 0.776 X_{11} = 0.571 X_{12} = - X_{13} = 0.867 X_{14} = 0.900
3	Multicolinearity	Tolerance; VIF	Tolerance > 0.1 VIF < 10	X_1 : tolerance = 0.361 VIF = 2.769 X_3 : tolerance = 0.361 VIF = 2.769	X_1 : tolerance = 0.361 VIF = 2.769 X_3 : tolerance = 0.361 VIF = 2.769
4	Autocorrelation	Durbin-Watson	-2 < DW < 2	1.684	1.961

Table 2. Estimation of parameters.

Equation	R square			
	O_i		D_d	
	X_1	X_3	X_1	X_3
Linear	0.914	0.417	0.890	0.368
Power	0.843	0.336	0.814	0.300
Exponential	0.830	0.305	0.802	0.270
Logistic	0.830	0.305	0.802	0.270

R^2 values of 0.953 and 0.950 mean that the independent variables (simultaneously) explain 95.3% and 95% of variances of the dependent modeled outputs, while the rest is not accounted for by the models. The standard errors 1.42311% and 1.36858% mean that the models were accurate to 98.58% and 98.63%; while the coefficient indicates the influence of partial variables (an individual predictor) on the dependent variable. With the significance threshold 0.05, it can be concluded that the population and per capita GRDP both affected generation and attraction of air passengers.

3.4 Fitted equations

The fitted linear regression regression results were as follows:

$$Y_1 = 6,3X_1 + 1,5X_3 - 97 \quad (1)$$

where: Y_1 = generation of air passengers
X_1 = population
X_3 = per capita GRDP

$$Y_2 = 6X_1 + 1,7X_3 - 113 \quad (2)$$

where: Y_2 = The attraction of air passengers
X_1 = population
X_3 = per capita GRDP

These results show that both generation and attraction of air passengers in this region were significantly affected only by population and per capita GRDP, among the candidate predictors tested. Increases in population and per capita GRDP tended to increase generation and attraction of air passengers in this region. The other candidate predictors were not proven to significantly affect generation/ attraction in this region.

3.5 Results of estimation

Estimates were made in the short term (for the next five years) and in the medium term (for the next ten years), based on the time series data over the past ten years. By 2022, generation and attraction in Papua are estimated to grow by 11.94% and 9.35% to 2,480,119 and 2,391,956 passengers, from the previous 2,215,508 and 2,187,506 passengers. By 2027, generation and attraction are predicted to grow by 26.03% and 29.14% to 3,125,610 and 3,088,936 passengers. For West Papua, by 2022 generation and attraction are predicted to grow by 81.95% and 70.85% to 1,743,807 and 1,669,894 passengers, from the previous 958,391 and 977,404 passengers. By 2027, generation and attraction are predicted to grow by 94.79% and 96.26% to 3,396,772 and 3,227,264 passengers (Table 4). These estimates are shown in Figure 2. These estimates provide a forecast of generation/attraction in the future. It is expected that this forecasted scenario can guide the decision-making concerning the development of airports and other infrastructure in the region.

4. Conclusions

The results show that out of fourteen independent candidate predictor variables expected to affect generation and attraction of air passengers in this region, only two variables were proven to significantly affect the modeled outputs. These predictor variables or regressors were population and per capita GRDP. Although Papua and West Papua are provinces very rich in natural resources (in the forms of forests, minerals, oil

Table 3. Regression output.

Model	R	R square	Adjusted R square	Std. error of the estimates	Unstandardized B	Sig.
Dependent variable : O_i						
1 (Constant)					-9.665	0.021
Population	0.976	0.953	0.944	1.42311	0.632	0.000
Per capita GRDP					0.149	0.012
Dependent variable : D_d						
1 (Constant)					-11.285	0.008
Population	0.975	0.950	0.941	1.36858	0.615	0.000
Per capita GRDP					0.174	0.004

Table 4. Estimation results.

Zone	2017		2022		2027	
	O_i	D_d	O_i	D_d	O_i	D_d
Papua	2.215.508	2.187.506	2.480.119	2.391.956	3.125.610	3.088.936
West Papua	958.391	977.404	1.743.807	1.669.894	3.396.772	3.277.264

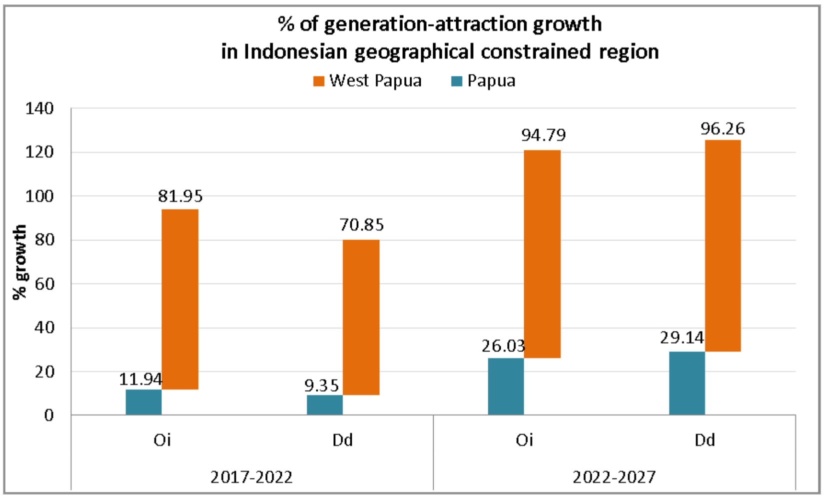

Figure 2. Percentage of generation-attraction growth in Papua and West Papua.

and natural gas, tourism, and marine resources), these factors do not affect the demand for air passengers in this region. Only the increases in population and per capita GRDP tend to significantly increase generation/attraction of air passengers in this region.

We argue that as long as the basic needs of people in this region cannot be accommodated by these two areas, then the community needs modes of transportation for travel to other regions. In fact, there are movement constraints due to the geographical constraints of the region. The only choice to fulfill their basic needs now is air transportation.

Therefore, we argue that the government must intervene in accelerating transportation development in these two regions. Both acceleration in the development of air transportation, as well as integration between modes. Moreover, given that the Papua Islands are very prone to landslides and erosion, and have a fault line due to interactions between the tectonic plates of Eurasia, the Indo-Australian and Pacific plates; this region has a high risk of tsunami as well as tectonic earthquakes. Proper development of air transportation capacity will not only support the community in meeting its basic needs but also contributes to disaster preparedness.

In addition, we also recommend full attention to the planning, implementation, and supervision of the implementation of pioneer flights in the Islands. The attention to the services and progress of this pioneering flight is relatively inadequate given its very important role in the national development process, namely as a means of establishing connectivity with remote areas. In addition to playing a role in increasing regional connectivity, this pioneer flight service is a link to the main route or feeder in the implementation of national air transport.

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