DETERMINATION OF PASSENGER LOAD FACTOR: THE CASE OF THAI AIRLINES

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Abstract

This research aims to investigate the relative factors affecting level of passenger loading factor for Thai airlines. Through literature review, factors affecting passenger loading factor were identified. Researcher included airline alliance status, number of global air incidents, number of flight departures airlines' selling and advertising expenses, revenue passenger kilometers, and number of passenger seats in the multiple linear regression model. Secondary data were collected from three major airlines of Thailand which are listed in the Stock Exchange of Thailand. By using ordinary least squares estimation, at 95 percent confidence level, the airline alliance status, air incidents, revenue passenger kilometers, and number of passenger seats are the significant variables that explain the passenger load factor.

Keywords: Passenger Load Factor (PFL), Airlines, Air Incidents, Airline Alliances, Thailand

I. Introduction

One of the key operating statistics of an airline is load factor, which determines the efficiency in carrying passengers and freights. High passenger load factor reflects well-managed available seats sold to passengers. In March 2016, International Air Transport Association (IATA) announced the strong passenger demand for air transport for international passenger market. The average international PFL was 79.7% in 2015 and rose by 1.0% in January 2016 (IATA, 2016).

Since passenger load factor (PFL) is a very important key performance figure, airlines target to produce high PFL while minimizing operating costs. It is interesting to explore relative factors affecting level of PFL and utilize them to determine PFL for Thai airlines to visualize opportunities for operating cost and performance efficiency's improvement. Benefits of this study is clearly contributed to Thai airlines. Realizing the factor influencing the load factor would lead them to better planning and forming necessary strategies in order to maintain or reach the desire level of future load factor.

This research aims to determine relativity of airline operating performances, expenses, and external factors to PFL of Thai major airlines by using multiple linear regression with ordinary least squares estimation. The first section dedicates to research's introduction and objective. The second section provides literature review on PFL and methodologies used to quantify PFL. The third section proposes a multiple regression model for PFL. The forth section describes data characteristics and data collection. The fifth section presents regression results, model improvement and discussion of results. The last section summarizes the research findings as well as offers recommendations.

II. Literature Review

Commercial airlines service in Thailand took place during 1910s, with Don Muang airfield (nowadays Don Muang International Airport) the major air hub. Thai Airways International Public Company Limited (THAI) was founded in 1959 as Thai Airways Company. The company was operated jointly between Thai government and Scandinavian Airlines System to provide international passenger air transport service. As a flag carrier of Thailand, THAI offers aviation related business services range from full-service passenger air transport, ground service, inflight-catering, air cargo service, and aircraft repairs and maintenance (THAI, 2015). Nine years after the foundation of THAI, Bangkok Airways Public Company Limited (BA) was established as Sahakol Air to provide contracted private air-taxi services. The company started offering schedule flight services in 1986 and changed airline's name to Bangkok Airways in 1989 (BA, 2015). The expansion of commercial airlines services was not appeared until the beginning of 2000s. As of 2016, there are 11 commercial airlines that offer domestic flight services and five commercial airlines that offer international flight services (Department of Civil Aviation, 2016).

Airport of Thailand Public Company Limited (AOT) has reported continuous growth in air traffic in terms of aircraft movement and number of passengers from 2009 to 2015 (AOT, 2015). Figure 1 presents passenger movement in six major international airports of Thailand during 2002 – 2016. Both growth in airlines services and passenger movements resulted in more intense competition between airlines, not only in Thailand but also worldwide. Figure 2 illustrates PFL comparison of four major airlines in Thailand: two full-service carriers (FSCs) and two low cost carriers (LCCs) during 2014 - 2016. Average PFLs for FSCs is 73.19 and average PFLs for LCC is 81.77, indicating better operating performance for LCC.

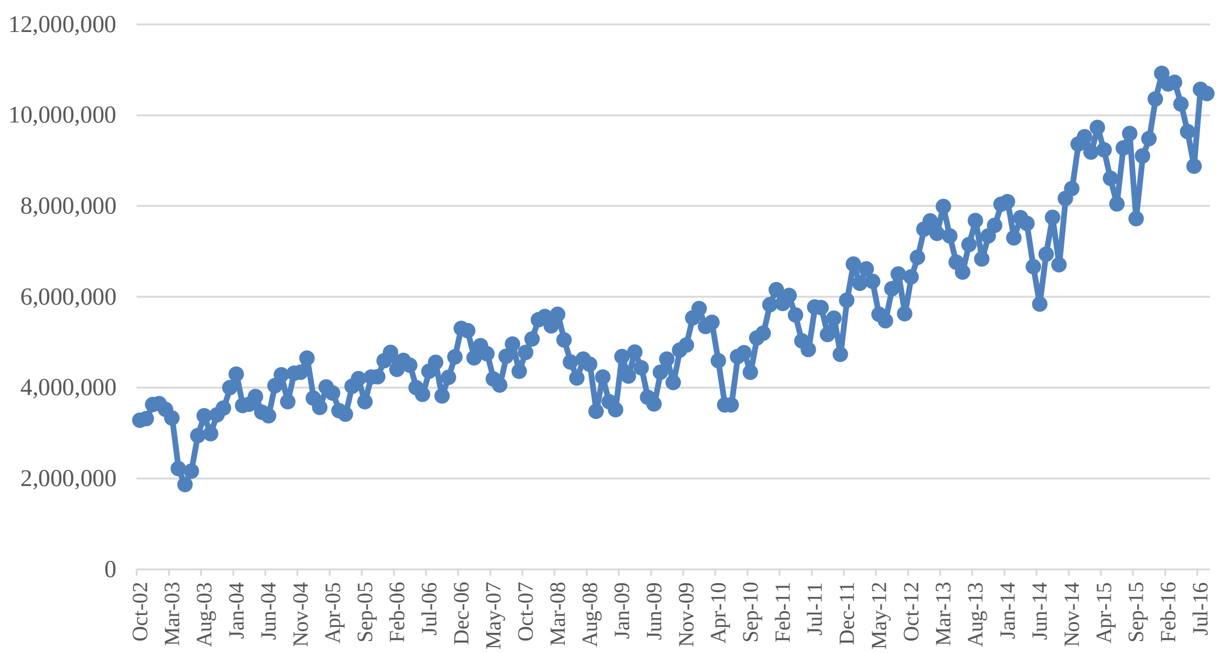

Figure 1 – Air Passenger Movement during 2002 – 2016

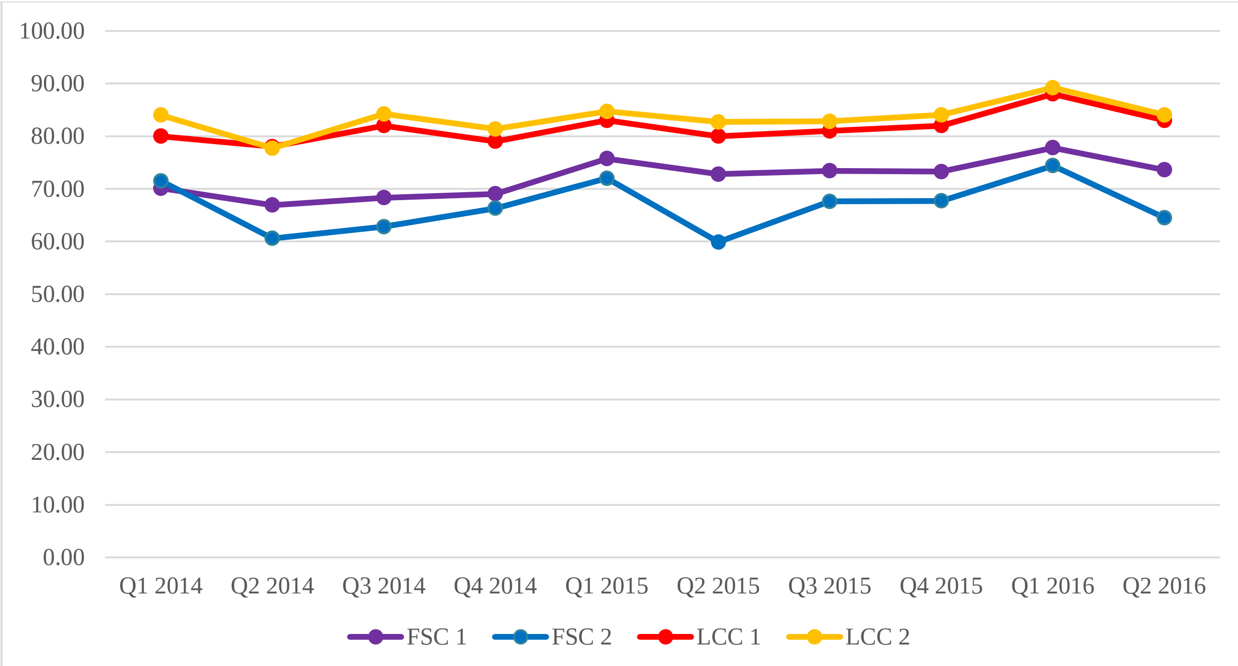

Figure 2 – PFL comparison between FSCs and LCC

Literatures concerning PFL in early period focused on airlines' costs and operating performance impact toward average PFL. Caves, Christensen, and Tretheway (1984) described that "higher load factor is associated with higher productivity levels". This means productivity factors such as number of seats and destination choices should played significant roles in determination of PFL.

Wensveen (2007) also described that "one of the most vital statistics in the airline business is load factor", which express "the relationship between available seat-miles and revenue passenger miles realized". PFL can also be influenced by economic recession, traffic growth, capacity limitation agreement, and seasonality.

PFL is also associated with airline scheduling and network planning. According to Mathaisel (1997), PFL was one of the schedule performance statistics. Cadarso and Marín (2013) also included PFL as part of their Integrated Robust Airline Scheduling Model. Evans and Schäfer (2014) used PFL to develop an airline network optimization model as a seat constraint.

According to literature review research carried out by Zuidberg (2014), most of PFL studies indicated negative relationship between the load factor and total airline costs. A number of studies also found that PFL has positive impact on operating margin. In the same research, one of the hypothesis was constructed as "A higher load factor leads to lower operating costs per aircraft movement". Based on econometric results in the work of Zuidberg (2014), it was concluded that increase in PFL does not affect aircraft operating cost.

PFL was applied as part of airline's cost and performance analysis in many ways. Tsai and Kuo (2004) included PFL as one of the variable to identify expected idle of passenger capacity, marketing variance and production variance for aircraft renewal and composition decisions. Due to the nature of operations, low cost carriers generally has higher PFL when compare with full-service carriers (Morrell, 2005). McLean (2006) claimed that PFL has relatively high effect toward operating efficiency, along with aircraft utilization, fuel efficiency, and yield management, which leaded to a suggestion that an airline can improve the poor PFL by withdrawing aircraft from service.

In terms of alliance, PFL was viewed as part of success factors. Chen and Chen (2003) concluded that parallel code-sharing of airlines resulted in higher PFL. Iatrou and Alamdari (2005) also explored the impact of alliances on airline operations by using five-scale ratings. PFL, which has been identified as one of the impacts, was positively influenced by the alliances on airline operations in general.

Apart from cost and operating performance, price also reflects PFL. Research conducted by Clark and Vincent (2012) revealed that in some airlines, prices are responsive to PFL as well as prices of competing airlines. Mumbower, Garrow, and Newman (2015) identified PFL as one of factors affecting passenger purchasing behavior for premium coach seats.

Safety is another issue that could have affected the PFL. Barnett and Curtis (1991) has investigated the association between domestic jet accidents in the United States and increasing PFL. Statistical results from 10 randomly chosen aircrafts showed that the higher the load factor, the greater the death risk per flight. Safety was also identified as one of attributes for flight choice (Hagmann, Semejin, and Vellenga, 2015). Out of 12 attributes, flight choice preferences are heavily dominated by non-stopover and safety, respectively. The researchers concluded that people prefer to travel with airlines that offer direct flights and have good safety records.

PFL was also applied to the Forecast of Aircraft Movement (FoAM) model proposed by Kölker, Bießlich, and Lütjens (2016). By putting the certain load factors into FoAM model, future frequency of flight segments can be calculated, under an assumption that the maximum PFL has to be 90% with decreasing growth of 0.01% per annum.

Different approaches were used to quantify PFL. In 2007, two researchers determined factors affecting load factor in airline industry. According to Jenatabadi and Ismail (2007), PFL is a measure of an airline's passenger carrying capacity. Researchers used data from seven Iranian commercial airlines with time span between 1997 and 2006; resulting in total of 70 observations, for the regression model. They defined mathematical definition of load factor as follows.

$$Load\ Factor = \sum_{i=1}^{r} \left(\frac{Number\ of\ carried\ passengers\ \times distance}{Available\ seat\ \times distance} \right) \times 100\%$$

Where *r* = the number of routes.

Number of carried passenger = number of passengers carried in the route between two cities or stations; either in one country or two different countries

Distance = distance between two stations and is measured by kilometer.

Available seat = number of available seats in the which depends on the kind of aircraft

Jenatabadi et al. (2007) developed a model for load factor including independent variables as follows.

- *Computerized System* is the number of agencies using computerized reservation system. It is labeled as System Location by Duliba, Kauffman and Lucas (2001) and it is lagged one year to take into account the learning curve of the travel agency, expecting that the full impact of automating a travel agency should be felt during the year after the automation occurs.
- *Average length* is the average distance in kilometer of the airline's flights between the city pairs.
- *Departures* is the number of departures in a year.
- *Organization* is a binary variable where 1 denotes private organization and 0 denotes governmental organization.
- *Advertising expenses* is the sum of expenses for each airline in a year.
- *Subsidy* is the amount of subsidy in US dollar given by Iran government to the airline companies.
- *Inflation rate* is the rate of increase of the average price level
- *Number of Seat* is the total number of seats for every airline
- *Change in Vehicle Kilometers* is the first difference of air transportation vehicle kilometers between year t and t-1.

The researchers computed generalized least squares solution for the model. Result showed that *Computerized System*, *Average Length*, *Organization*, *Subsidy* and *Change in Vehicle Kilometer* are significant while *Departures*, *Advertising Expenses*, *Inflation Rate* and *Number of Seats* are not significant in explaining the variation in the load factors. Researchers also suggested that Iranian airlines should increase their investment in computerized reservation system and have proper operation planning.

Devriendt, Burghouwt, Derudder, de Wit, and Witlox (2009) use demand and supply data to compute PFL for transatlantic airlines. The data was derived from the Official Airline Guide (OAG) and Marketing Information Data Transfer (MIDT) database. Data set from OAG was treated as supply data while data from MIDT was treated as demand data. Variables associated with the load factor are origins and destinations of the direct flights; operating alliances that was active in 2001; total number of passengers that book flights; seat capacity; and flight frequency. By using the combined OAG-MIDT database, the calculated load factors underestimate the actual the load factor by approximately 10%.

III. The Regression Model

Researcher developed multiple regression model by using factors defined or discussed by Iatrou et al. (2005), McLean (2006), Jenatabadi et al. (2007), Devriendt et al. (2009), Zuidberg (2014), and Hagmann et al. (2015). Researcher introduced *Air incident* as one of independent variables to verify the pattern proposed by Barnett et al. (1991), since this research was conducted by using only 10 incidents occurred during 1975 – 1989. Researcher developed a regression model based on the regression model proposed by Jenatabadi et al. (2007) by dropping some outdated and/or invalid independent variables and adding new independent variables, resulted in total of six independent variables. The multiple regression model for PFL can be written as follows.

$$PFL_t = \beta_0 + \beta_1 AirIncident_t + \beta_2 Alliances_t + \beta_3 Departures_t + \beta_4 Expenses_t + \beta_5 RPK_t + \beta_6 Seats_t + \varepsilon_t$$

Where

PFL is the passenger efficiency ratio. It is calculated by dividing number of carried passengers by total available seat.

Air Incidents represents the number of worldwide air accidents and incidents. The accidents and incidents, either investigated or under investigation, are concerned with the safety issue in air transport. This variable is an experimental external factor that could have affect the load factor and was discussed by Hagmann et al. (2015).

Departures represents the number of departed flights. This variable is an internal factor that presents airlines' operations and was defined by Jenatabadi et al. (2007).

Alliances is a binary variable where 1 denotes the airlines with alliance (Part of Star Alliance, Oneworld, SkyTeam, Vanilla Alliance, U-FLY Alliance, and Value Alliance) and/or affiliations (airlines with subsidiaries, being subsidiary of an international airline or part of international airline group) and 0 denotes airlines without alliance. Airlines with code share agreement are considered as non-alliance. This variable was discussed by Iatrou et al. (2005).

Expenses represents total selling and advertising expense of the company (unit in millions). This variable is an internal factor that indicates airlines' operating costs and was used by Jenatabadi et al. (2007) and Zuidberg (2014).

RPK stands for revenue passenger kilometers. The variable represents the total revenue passenger kilometers (unit in millions) which calculate by multiplying number of passengers that generate revenue to the airline by the distance travelled in kilometers. This variable directly reflects productivity of the airline and was discussed by McLean (2006).

Seats represents the total number of passenger seats in each period. This variable is an internal factor that exhibits airlines' operations and was mentioned by Jenatabadi et al. (2007) and Devriendt et al. (2009).

IV. Data Collection

This research used secondary data from four leading airlines in Thailand that yield highest number of passengers at Suvarnabhumi International Airport and Don Muang International Airport (AOT, 2015). All airlines are registered as Thai organization and listed in the Stock Exchange of Thailand. Characteristics of airlines are described in Table 1. Airlines were ranked by number of passenger movement for international and domestic flights at Suvarnabhumi International Airport and Don Muang International Airport (AOT, 2015), with exclusion of non-Thai airlines.

Table 1 – Characteristics of Airlines

Airlines Ranking*	**Type**	**Organization**	**Listed Year**	**Major Shareholder**	**Alliances and Affiliations**
1	FSC	Public Company	1991	Government	Part of airline alliance Owned two affiliated airlines
2	LCC	Public Company	2012	Family shareholders	Part of airline group Affiliated airline of international LCC
3	LCC	Public Company	2013	Public Company	Affiliated airline of Thai FSC
5	FSC	Public Company	2013	Family shareholders	None

**4th ranking airline is a privately held company. Due to data availability and reliability issues, researcher excluded the airline from the analysis.*

The data were collected in quarterly manner. Because one of the airlines was listed in the Stock Exchange of Thailand in the last quarter of 2013, data set were limited. Observations are data from the first quarter of 2014 to the second quarter of 2016. Financial and operating statistics data are publicly available in each airline's investor relation websites. Air Incidents data were obtained from SKYbrary. All data, despite being time-series data, were treated as cross-sectional data.

V. Regression Results and Discussions

A. Multiple Linear Regression

By using ordinary least squares estimation with 95% confidence level, the regression result is displayed in Table 2.

Table 2 – Multiple Linear Regression Result

Source	SS	df	Ms
Model	2070.0136	6	345.0023
Residual	282.2109	33	8.5518
Total	2352.2245	39	60.3134

Observations	=	40
F(7, 67)	=	40.34
Prob. > F	=	0.0000
R-squared	=	0.8800
Adj. R-squared	=	0.8582
Root MSE	=	2.9244

PFL	Coefficient	Std. Err.	t	P>|t|	[95% Conf. Interval]	
Air Incidents	-0.3589	0.1261	-2.8500	0.0080	-0.6154	-0.1023
Alliances	14.3921	2.1224	6.7800	0.0000	10.0741	18.7102
Departures	0.0000	0.0001	-0.4700	0.6440	-0.0001	0.0001
Expenses	-0.0024	0.0042	-0.5700	0.5730	-0.0110	0.0062
RPK	0.0036	0.0012	3.0900	0.0040	0.0012	0.0060
Seats	-0.0029	0.0009	-3.2100	0.0030	-0.0047	-0.0010
Constant	70.6451	1.8418	38.3600	0.0000	66.8979	74.3922

Since Prob. > F= 0.0000, this mean the model itself is significant and all variables explain 88.00% of the variance in PFL.

Out of six variables, four variables are significant in explaining PFL, which are *Air Incidents* (p-value = 0.0080), *Alliances* (p-value = 0.0000), *RPK* (p-value = 0.0040) and *Seats* (p-value = 0.0030). This also shows that the number of flight departures and selling and advertising expenses is not significant in explaining the PFL and thus, coincide with the model and conclusion of Jenatabadi et al. (2007).

B. Correlation Test

We need to identify if there is any high correlation among variables. As presented in Table 3, it can be observed *Seats* and *RPK* is the most extreme positive correlated pair (R = 0.9968), follows by *Seats* and *Expenses* (R = 0.9768), and *RPK* and *Expenses* (R = 0.9704). *PFL* and *Expenses* (R = -0.3719) is the most negative correlated pair. Zero value of R for *Air Incidents* and *Alliances* means there is no relationship between these two variables.

Table 3 – Pearson's Correlation Matrix

	PFL	Air Incidents	Alliances	Departures	Expenses	RPK	Seats
PFL	1						
Air Incidents	-0.2165	1					
Alliances	0.6960	0.0000	1				
Departures	0.3058	-0.1334	0.3059	1			
Expenses	-0.3719	-0.0305	0.2318	-0.0835	1		
RPK	-0.1887	-0.0339	0.4248	-0.0029	0.9704	1	
Seats	-0.2330	-0.0140	0.3986	-0.0166	0.9768	0.9968	1

Because of extreme positive correlation between *Seats* and *RPK*, *Seats* and *Expenses*, and *RPK* and *Expenses*; researcher eliminated each variable at a time, as well as all three variables from the model to see if the model can be improved. The multiple linear regression results are compares in Table 4.

Table 4 – Comparisons of Multiple Linear Regression Results

Modification	Dropped Variables	Prob. > F	R-squared	Root MSE
1	*Expenses*	0.0000	0.8788	2.8952
2	*Expenses*, *RPK*	0.0000	0.8453	3.2247
3	*Expenses*, *Seats*	0.0000	0.8271	3.4088
4	*RPK*, *Seats*	0.0000	0.8403	3.2758
5	*Expenses*, *RPK*, and *Seats*	0.0000	0.5359	5.5067

It can be seen that, without *Expenses*, All independent variables are significant in explaining PFL. Value of r-squared is slightly lower than the r-squared of the original model, indicating the lower significant of each factors to PFL. Root mean square error (Root MSE) is also slightly improved. Dropping *Expenses* and *RPK*, *Expenses* and *Seats*; and *RPK* and *Seats* also resulted in lower r-squared values and higher root mean square errors. Dropping all three variables yielded significantly lower r-squared values and higher root mean square errors. Since it can be proved that the elimination of *Expenses* does not affect the model as a whole, researcher will continue to use the model that exclude *Expenses* (Modification 1) for further analysis.

C. Tests for Heteroscedasticity

Because the time-series data are treated as cross-sectional data, tests for heteroscedasticity are required. There are several tests for heteroscedasticity but this research applied the two most popular tests: Breusch-Pagan test and White test. Both tests were deployed with the model without *Expenses* variable.

For Breusch-Pagan test for heteroscedasticity, the null hypothesis is defined as H_0: Constant variance. The variables are fitted values of the load factor. The chi-square (1) or $\chi2$ (1) is 3.90 and Prob. > $\chi2$ is 0.0483. Therefore, the null hypothesis have to be rejected.

Another test for heteroscedasticity is Cameron & Trivedi's decomposition of IM-test or White test. By setting the null hypothesis as H_0: homoscedasticity, against H_a: unrestricted heteroscedasticity. The chi-square (19) or $\chi2$ (19) is 18.15 and Prob. > $\chi2$ is 0.5125. Therefore, the null hypothesis cannot be rejected.

Since in Breusch-Pagan test for heteroscedasticity, the null hypothesis have to be rejected, it can be concluded that the variance of the error terms is not constant. However, White test revealed that heteroscedasticity does not exist. Conflict in test results suggested that the regression model should be further revised.

D. Model Improvement

Because there are heteroscedasticity in data, researcher tried to improve the model by dropping variables that cause heteroscedasticity and inconstant variance of the error terms. The test results are displayed in Table 6. Modification 1 are tests for heteroscedasticity of the original model. In both tests, the null hypothesis cannot be rejected. Similarly, by dropping the variable *Expenses* and *Seats*, the null hypothesis in both tests cannot be rejected. On the other hand, dropping out the variable *Expenses* and the variables *Expenses* and *RPK* resulted in rejecting the null hypothesis in the Breusch-Pagan Test. Interestingly, by dropping out *RPK* and *Seats* (Modification 5), which are significant variables in explaining PFL in the original model, the model is not only pass both tests for heteroscedasticity but also resulted in having *Expenses* as one of significant variable in explaining PFL (p-value = 0.0000).

Table 6 – Comparisons for Test for Heteroscedasticity

Modification	**Dropped Variables**	**Test for Heteroscedasticity**					
		Breusch-Pagan Test			**White Test**		
		$\chi2$	df	Prob. > $\chi2$	$\chi2$	df	Prob. > $\chi2$
1	-	3.77	1	0.0521	25.39	26	0.4970
2	*Expenses*	3.90	1	0.0483	18.15	19	0.5125
3	*Expenses*, *Seats*	3.50	1	0.0614	12.78	13	0.4652
4	*Expenses*, *RPK*	3.85	1	0.0498	12.09	13	0.5207
5	*RPK*, *Seats*	3.52	1	0.0606	15.47	13	0.2792

Therefore, the researcher will continue using the original model since the model yields the highest r-squared value and the lowest root mean square error. The tests for heteroscedasticity confirmed that the variance of the error terms is constant and heteroscedasticity does not exist. It can be concluded that *Air Incidents*, *Alliances*, *RPK*, and *Seats* are significant in explaining the PFL for Thai airlines.

Alliances is one of the variables with positive coefficient, which means PFL will decrease in absent of airline alliance and coherent with the study of Chen et al. (2003) and Iatrou et al. (2005). *RPK* also has positive coefficient. The coefficient number is quite small and the variable has negative correlation with PFL. Negative coefficient of *Air Incidents* can be interpreted that the higher the number of global air incident, the lower the PFL for Thai airlines. Additionally, *Seats* has negative coefficient. The coefficient number is also small and the variable has negative correlation with PFL. Negative correlations between *RPK* and PFL; and *Seats* and PFL is still rational because both variables are the determinations of PFL. Decreasing in both value can still yield higher PFL. When passenger traffic and number of available seats of airlines negatively reacted with PFL but PFL increases, this means revenue-generating passengers (numerator) decrease in smaller proportion in compare with number of available seats of airlines (denominator).

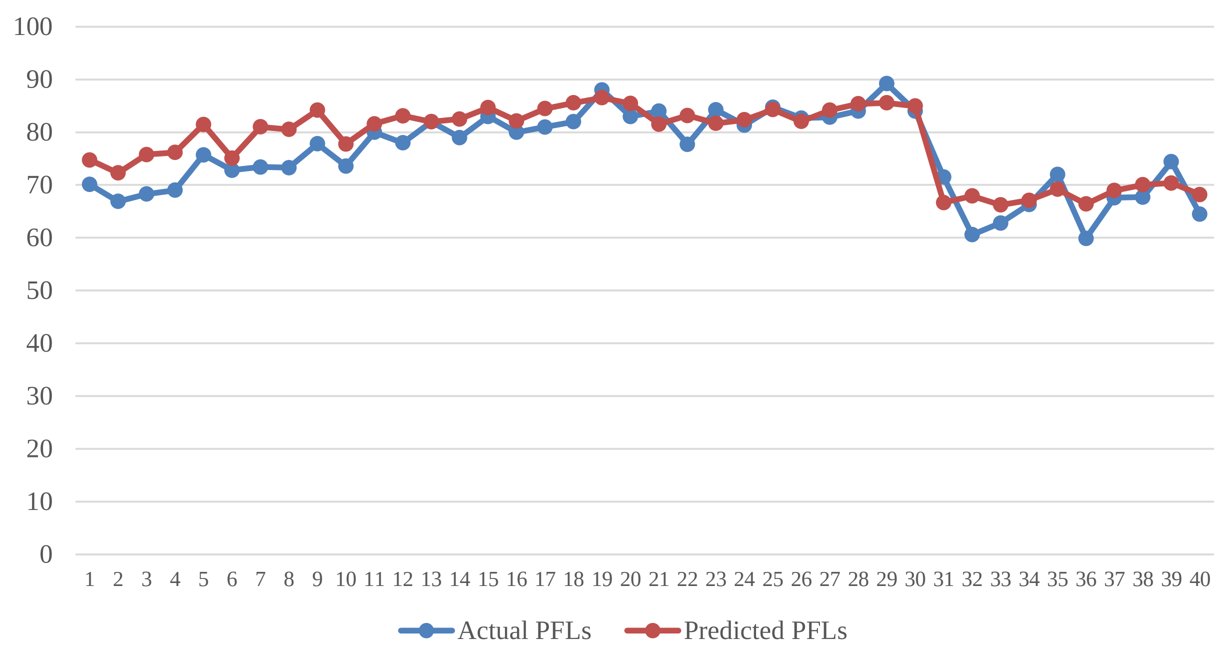

Figure 3 – Comparison between Actual PFLs and Predicted PFLs

Figure 3 compares the actual PFLs with the predicted PFLs, which can be observed that the predicted PFLs resemble the data pattern of the actual PFLs. Although the four independent variables can explain only 88% of dependent variable, and root mean square error is 2.9244, the average error in this model is approximately -3.36%, indicating slight underestimations for PFLs in this model. On average, the model perform better determinations for LCCs than FSCs.

VI. Conclusion and Recommendations

PFL for Thai airlines can be determined by using four variables: air incidents; airline alliance status; RPK; and number of seats, which lead to a conclusion that decreasing number of global air incidents, existence of airline alliance, and slight increase in RPK with small drop in number of available seats of airline will resulted in higher PFLs. Despite the fact that low cost variable was excluded from the regression model, it is undeniable that low cost carriers will generally yield higher PFL than full-service carriers (Morrell, 2005).

By taking a closer look into the air incidents data, it can be observed that out of 591 air incidents over the past ten years. There are only one major incidents that cause severe casualties occurred in Thailand during that period. The incident of MD-82 aircraft crashed at Phuket International Airport in 2007 was operated by One Two Go Airlines, which is not part of this research. Because the air turbulence experience of a flight bounded from Hong Kong to Bangkok, and the runway excursion of a flight bounded from Guangzhou to Bangkok are not taken in to account (both of them occurred in 2013), it is undeterminable whether the non-severe air incidents influence the PFL or not. Therefore, as long as the air incident exists, it can be presumed that the higher the number of global air incidents, the more passengers will be attracted to Thai airlines. Because people prefer to travel with airlines that have good safety (or air incident) records, it is recommended that the airlines should strictly follow safety rules and regulation in accordance with safety standard set by International Civil Aviation Organization (ICAO) to maintain the desirable level of PFL.

There are some remarks about the analysis of PFL. First, researcher is unable to obtain code share seat in proportionate to seat sold by Thai airlines. The data should support the proposition that the airline alliances have positive affect the passenger load factor because the cooperation between airlines should have increased number of passengers and the load factor. In this research, only the existence of airline alliances is known and the variable was set as binary, detailed data concerning code share seats should provide more insightful analysis.

Another factor that researcher did not take into account is the pricing strategies of airlines. It would be interesting to quantify the effect of price in various situations such as prices of the airlines against their rivals; pricing and zero fare promotion; and prices comparison between incumbent airlines the new comer airlines; to see whether this factor have any significant effect to PFL.

The last remark concerned with data issue. Due to availability of data of a commercial airline that was listed in the Stock Exchange of Thailand in the last quarter of 2013, researcher can obtain only 10 observations from the airline, resulted in using the data from the same period of the other three airlines. Future research when there is more data available is recommended to ensure model's reliability. Additionally, researcher limited scope of research to airlines that were listed the Stock Exchange of Thailand, not only because data concerning financial and operations are thoroughly verified by the Securities and Exchange Commission, but also the accessibility of data. Research can also be extended to cover global airlines, particularly for FSCs and LCCs, which the later focus heavily in maintain high level of PFL.

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