JOURNAL OF INTERNATIONAL LOGISTICS AND TRADE
Volume 13, Number 1, April 2015, pp.3~30

Comparative Analysis of Operational Efficiency of Major Airlines in Asia-Pacific Region*

Zhen Gong**, Tae Seung Kim***

Abstract

This paper uses various Data Envelopment Analysis (SBM-DEA) approaches to study the efficiency of major airlines in Asia-Pacific region. To evaluate the operation efficiency of fourteen major airlines in Asia-Pacific region from 2003-2011, Available Seat Kilometers(ASK), Available Ton Kilometers(ATK), the number of employees are used as input factors, Revenue Passenger Kilometers(RPK), Revenue Ton Kilometers(RTK), the amount of Sales are used as output factors.

The non-radial SBM-DEA (Slacks-based Measure of Efficiency) model was able to provide a more comprehensive efficiency of combining economic performance and regional difference. And it was also able to capture slack values in input excess and output shortage.

The results demonstrate that Korea and Japan airlines are operated efficiently and could be regarded as the benchmarking airlines. On the other hand, most of the China and ASEAN airlines are deemed to be inefficient. Also analyzing slacks may be more suitable way for the evaluation or suggestion of an improvement scheme for the inefficient airlines. The excess of labor is the major cause of the airlines' inefficiency.

Key Words: *Operational Efficiency, Slacks-based measure (SBM), Data Envelopment Analysis (DEA), Asia-Pacific airlines*

JEL codes: *D24, L93, O53, R41*

* This work was supported by Inha University.

** Master, Graduate School of Logistics, Inha University, 100 Inha-ro, Nam-gu, Incheon, Korea, E-mail: gz8906@hotmail.com

*** Corresponding author, Associate Professor, Graduate School of Logistics, Inha University, 100 Inha-ro, Nam-gu, Incheon, Korea, E-mail: todang@inha.ac.kr

1. Introduction

Asia-Pacific region is said to be one of the fastest growing and the largest aviation markets in the world. Asia-Pacific airlines today carry a quarter of global air passenger traffic and two-fifths of global air cargo traffic, and are a major collective force in international aviation market. In terms of profitability, data from IATA(The International Air Transport Association) shows that Asia Pacific airlines account for a half of the global industry's profits amounting to about $10 billion out of $18 billion in 2010, and $2.1 billion out of $4 billion in 2011, when industry profits have been severely squeezed by rising oil prices and economic crisis.

The commercial success of those Asian airlines today can be attributed to strong financial discipline, strict vigilance over costs, as well as superior product offerings at very competitive prices. At the same time, the dynamic economic environment in Asia has also encouraged innovative partnerships and arrangements to meet the growth in travel demand in the region.

Accordingly, the main purpose of this study is to evaluate the operational performance of the major airlines in Asia-Pacific region. More precisely, this study analyzed 3 issues to be considered related with the performance of those airlines. First, the operational efficiency of the major airlines in Asia-Pacific region is observed. Second, the factors influencing the airline operational efficiency is investigated. Finally, the characteristics and issues in each national market which are related with the operational differences in the efficiency ranking are examined.

In order to accomplish these objectives, a panel data including 14 major airlines in the region over the 9 years (2003-2011) was collected. Major method of analysis is the data envelopment analysis (DEA) using 126 decisions making units (DMU) in total. Especially this study used the non-radial slack-based measure approach (SBM-DEA) as well as the traditional CCR, BCC models.

This paper consists of 6 sections, and the content of each section is as follows. In Section 2, we review existing literatures related with the DEA and efficiency evaluation on airlines. Section 3 describes the applied methodologies in this study, basic DEA and SBM (slack based measure) for the efficiency, and the data used in the models. Section 4 summarizes the results of empirical study and their policy implications. Finally, Section 5 concludes the paper by suggesting the limitations and further research areas.

2. Literature Review

2.1 Literature Review on DEA

There are a large number of studies measuring the productivity and efficiency of an industry using a range of parametric methods such as traditional regression analysis, stochastic frontier approaches(SFA), or a range of non-parametric analysis such as traditional partial productivity or unit cost measurement, total factor productivity (TFP) methods, and Data Envelopment Analysis (DEA) methods.

In terms of the methodologies adopted to measure the efficiency and productivity of airlines, most of studies have used the Data Envelopment Analysis (DEA) method. Few other authors have adopted the Stochastic Frontier Analysis (SFA) method, which measures technical efficiency through estimating a production function. While the DEA method is flexible in accounting for multiple inputs and outputs, it is usually criticized for being non-statistical as it does not take into account the measurement error in the estimation of efficiency. The SFA method, on the other hand, is statistical method that can address the problem of DEA, but is less flexible in accounting for multiple outputs.

In 1957, Michael Farrell presented a new method of measuring the productive efficiency of firms or DMUs (decision-making units) to the Royal Statistical Society. Farrell constructed a piece-wise linear technology representing the best practice methods of production and then used linear programming (LP) to estimate a radial measure of technical efficiency.

Two decades later, Charnes et al. (1978) first proposed the original Constant Return to Scale Data Envelopment Analysis (CCR-DEA). It is a nonparametric approach and measures relative efficiency of decision-making units (DMUS) by comparing multiple inputs with a single output (Cooper er al., 2000). Later, Banker et al. (1984) extended it to the Variable Return to Scale DEA (BCC-DEA) model. Since then, numerous applications extensions and modifications of DEA have appeared in professional journals and books. The DEA is used to identify the best practice within the set of comparable decision-making units (DMUs) and form an efficient frontier.

The radial model adjusts all inputs and outputs by the same proportion to efficient targets; thus, it does not provide information regarding the efficiency of specific inputs or outputs involved in the production process. Moreover, radial efficiency measures neglect slack variables, lead to biased estimations and has a weak discriminating power for ranking and comparing decision making units (DMUs). Because of these limitations, recent studies have tried to develop non-radial DEA approaches.

Tone (2001) first introduced the theory and methodology of a slacks-based measure (SBM). In contrast to the CCR and BCC measures, which are based on the proportional reduction (enlargement) of input (output), SBM deals directly with input excess and output shortfall of the DMU, which is called slacks. The SBM projects the DMU to the furthest point on the efficient frontier, in the sense that the objective function is to be minimized by finding the maximum slacks.

Therefore, it is, in principle, a non-radial model. As Tone claimed, "it is unit invariant and monotone decreasing with respect to input excess and output shortfall". Moreover, he stated that "the SBM is reference-set dependent. The measure is determined only by its reference-set and is not affected by statistics over the whole data set as in the traditional DEA models".

Fukuyama and Weber (2009) developed a generalized measure of technical inefficiency which refer to as the directional SBI (slacks-based inefficiency) accounting for all slacks in the input and output constraints. This measure is related to the directional technology distance function. The directional distance function seeks the maximum non-radial expansion in outputs and contraction in inputs for a given directional (scaling) vector.

The popularity of DEA can be attributed to the fact that:

(1) It allows for the assessment of multi-factor productive efficiencies through an effective integration of multiple inputs and outputs factors within a single efficiency score via the use of flexible weights or multipliers chosen through the solution of the model itself;

(2) DEA does not impose a parametric structure on data;

(3) DEA does not have heavy data requirements.

In essence, DEA allows for the assessment of multi-factor productive efficiencies using a single efficiency score established via the use of weights or multipliers selected on sound basis. Instead of having a subjectively defined weight assigned a-priori, DEA allows each decision making unit (DMU) to choose their own most favorable weights subject to the simultaneous consideration of other DMU's efficiency scores, relevant constraints and objectives. Furthermore, data measured in different units can be used simultaneously within a DEA model

Although DEA is a popular tool owing to its main advantages over the non-parametric index number and parametric model estimation approaches, the methodology is not without its shortcomings.

(1) Being an extreme point technique in which the efficiency frontier is formed by the actual performance of best performing DMU, efficiency scores are highly sensitive to even small errors in measurement. Where sample size is small, it would result in

a large proportion of DMU's having an efficiency score of 1.

(2) DEA does not explain the cause of the underlying sources of efficiencies and inefficiencies. Also, by constructing a deterministic frontier, any deviation from the frontier which is interpreted as inefficiency may in actual fact be due to random factors.

2.2 Literature Review on Airline Efficiency by using DEA

Many of recent researches in the aviation industry have applied DEA to evaluate operational performance. They can be classified into 3 groups by the major purposes of the researches.

The first group tried to evaluate just the efficiency of airline industry. Scheraga (2004) investigated whether relative operational efficiency implied superior financial mobility. He used DEA to derive efficiency scores for 38 airlines in North America, Europe, Asia and the Middle East, and found that the relative operational efficiency did not inherently imply superior financial mobility. Barbot et al. (2008) used DEA and total factor productivity (TFP) to analyze the efficiency and productivity of the 49 member airlines of IATA. The study found that low-cost carriers perform more efficiently than full-service carriers, and larger airlines are more efficient than smaller ones. With respect to geographic areas, the author noted that the European and American carriers were more effective than airlines in Asia Pacific and China/North Asia.

There is the second group who tried to complement the shortcomings of the DEA by using other methodologies combined with DEA. Barros and Peypoch (2009) applied DEA to evaluate the efficiency of 27 airlines in the Association of European Airlines (AEA), from 2000 to 2005, and they used the bootstrapped truncated regression analysis to find out the factor influencing the efficiency of airlines. The study found that almost all European airlines operated at a high level of pure technical efficiency and scale efficiency. In the second stage, the study used bootstrapped truncated regression and noted that population and network alliances are the most important influences on the efficiency of airlines. Merkert and Hensher(2011) applied a two-stage DEA approach, with partially boot-strapped random effects Tobit regression in the second stage to evaluate key determinants factors impact on costs and technical efficiency. It was found that airline size and key fleet mix characteristics are more relevant to successful cost management of airlines since they have significant impacts on all three types of airline efficiency: technical, allocative and ultimately, cost efficiency. The results also show that despite the fuel saving benefits of younger aircraft, the age of an airline's fleet has no significant impact on its

technical efficiency, but does have a positive impact on its allocative and cost efficiency.

The third group tried to verify the sources of the differences of rankings by explaining the gaps with various variables added. Kwon and Choi (2011) applied CCR and Super-SBM models to measure the relative efficient measurement of carrier operating product in low-cost and full-service carrier. By using Super-SBM considering slacks, the DEA is able to find out which airline is less efficient than others, Besides, it gives an opportunity to employ benchmarking by searching appropriate DMU based on the ranking analysis. Assaf and Josiassen (2011) measures and compares the efficiency and productivity of European and U.S airlines, over the period from 2001 to 2008. They measure efficiency by estimating a Bayesian distance frontier model subject to regularity constraints. Productivity estimates are also derived parametrically based on the estimates of the distance frontier model. The efficiency and productivity results based on the constrained model indicate that European Airlines have slightly higher efficiency and productivity growth than U.S. airlines. A comparison based on type of airlines indicates that low-cost airlines are on average more productive and efficient than full-service airlines.

Barros and Couto (2012) used Malmquist index and Luenberger indicator to evaluate productivity changes of European airlines, combining operational and financial variables from 2000 to 2011. The analysis suggests that most European airlines did not experience productivity growth between 2001 and 2011. Apart from the impact of the external environment, the managerial causes of technical efficiency may have been due to variations in the strategies adopted by the different airlines, the networks served, or differences in their historic resource base resources. Wu and He (2013) use DEA to explore the impact of an international focus, the proportion of cargo traffics and the level of salaries on the operational efficiency of Chinese airlines and other non-Chinese airlines. To investigate the impact of environment variables, a two-stage model when efficiency is measured in the first stage, and then regression is used to examine the effect of environmental variables on these efficiency scores in the second stage. The results show that an international focus has a negative impact, while the level of salaries has a positive impact. Also, there is an inverted U-shape relationship between efficiency and the proportion of cargo traffic.

Table 1.
Literatures on Airline Efficiencies by Using DEA

Authors	Subject of Analysis	Model
Scheraga (2004)	38 airlines in North America, Europe, Asia and the Middle East	DEA and Tobit regression
Barbot , and Costa (2008)	49 member airlines of IATA	DEA-BCC and total factor productivity (TFP)

Authors	Subject of Analysis	Model
Barros and Peypoch (2009)	27 airlines in the Association of European Airlines(2000-2005)	DEA and bootstrapped truncated regression
Kwon and Choi (2010)	6 major airlines and low-cost carrier in Korea	DEA-CCR, Super SBM
Merkert and Hensher (2011)	58 of the largest passenger airlines(2007-2009)	DEA and Tobit regression
Assaf and Josiassen(2011)	31 airlines in U.S and Europe (1999-2008)	Bootstraped Malmquist with two stage regression
Barros and Couto (2012)	23 European Airlines (2000-2011)	Malmquist and Luenberger productivity measures
Wu and He (2013)	12 Chinese and non-Chinese airlines (2006-2010)	DEA and bootstrapped truncated regression

The literature review shows that the numerous studies have analyzed the productivity, efficiency and competitiveness of the airlines based on DEA. However, the empirical studies on the operational efficiency of Asia-Pacific airlines have not been conducted and the SBM-DEA model, particularly Directional SBM-DEA model, has not been used widely.

Another approaches on the competitiveness of airlines, especially of the airlines in Asia-Pacific regions, can be found in Lee and Hyun (2014) and Park and Ha (2013). Lee and Hyun(2013) carries out a network analysis by using the data on centrality and community modularity of each airport in the region. But, they don't capture the efficiency of airlines directly, hence this paper would complement the result of their findings. Park and Ha (2013) uses the exploratory factor analysis and multiple regressions to verify the service quality of air cargo carriers. But they do not treat the service quality of each airline, but calculate the weight of several aspects related with the service quality.

To fill up the gap in the literature, the objective of this study is to estimate the Asia-Pacific airlines operational efficiency use the slacks based models. We uses the SBM-DEA model to capture the more accurate efficiency of airlines and tries to find out the policy implications based on the results.

3. Model and Data

3.1 Model; SBM-DEA (Slacks Based Measure) Model

3.1.1 The Non-Oriented SBM-DEA Model

Radial efficiency measures neglect the slack variables that may overestimate efficiency when there is non-zero slack. In order to overcome this limitation, recent studies developed non-radial DEA approaches.

The slacks-based measure (SBM) is a non-radial approach with desirable features. It directly accounts for input and output slacks in efficiency measurement, with advantage of capturing the whole aspect of inefficiency. In contrast to radial efficiency measures, which are based on the proportional reduction (enlargement) of input (output), SBM deals directly with input excess (potential reduction) and output shortfall (potential expansion) of observation, called slack variable. The SBM projects the observations to the furthest point on the efficient frontier, in the sense that the objective function is to be minimized by finding the maximum amounts of slacks. <Fig 1> shows the difference between the radial efficiency measure and the SBM-efficiency measure.

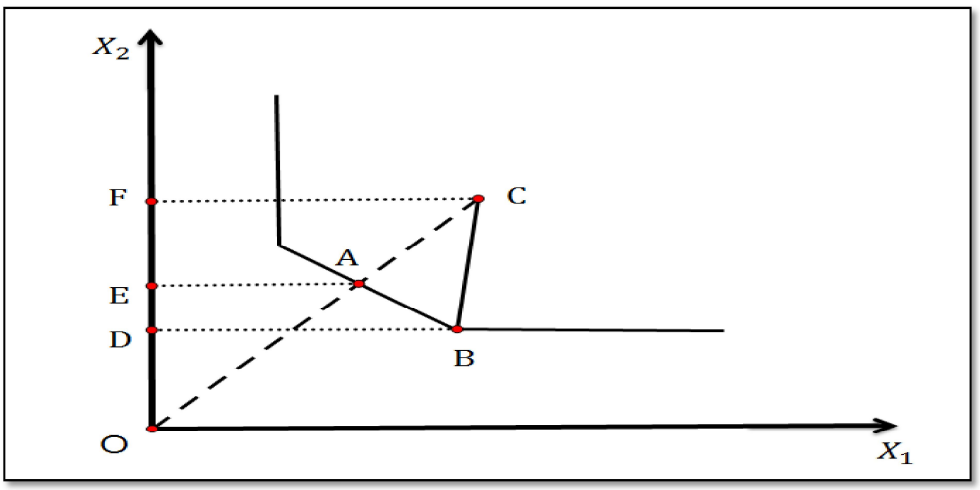

Fig 1.
Illustration of Radial Efficiency versus SBM Efficiency

We assume that the piecewise linear frontier is the combinations of inputs X_1 and X_2 that produce the same total output. All points on the frontier are technically efficient. The point within the isoquant curve is inefficient because they use more inputs to produce the same output.

Therefore, point ‘‘C’’ is not an efficient point. The radial efficiency measures adjust point ‘‘C’’ to efficient point ‘‘a’’ through origin and measures its efficiency score as ‘‘OA/OC.’’ A major problem with the radial efficiency method is that it does not provide efficiency of the specific inputs and all of the inputs’ efficiencies are measured at the same proportion ‘‘OA/OC.’’ For instance, the efficiency score is measured by ‘‘OE/OF’’ equals to ‘‘OA/OC”.

On the other hand, SBM is a non-radial efficiency measure that deals directly with the input excess and output shortfall of the observation, known as slack variables. It projects the observations to the ‘‘furthest point’’ on the efficient frontier, as shown in Fig. 2. Assuming that the furthest point in the frontier from point ‘‘C’’ is point ‘‘B’’, in which case the input slack is ‘‘DF’’ referring to the potential reduction from the real input ‘‘OF’’ to the target input ‘‘OD’’. Our SBM energy efficiency of point ‘‘C’’ is measured by ‘‘OD/OF’’ which is smaller than its radial score ‘‘OE/OF’’.

Assumed that there are n DMU and let $x_{ij}$and y_{ij} denote the amount of input i of airlines j and the amount of output i of airline j with j=1.2,⋯,n .The metrics of them are denoted as X and Y and defined as $X=(x_{ij})\in R^{m\times n}$, $Y=(y_{ij})\in R^{s\times n}$ and $X>0$, $Y>0$. The production possibility set is described as follow:

$$P=\{(X,Y)|x\geq X\lambda, y\leq Y\lambda, \lambda\geq 0\}$$

Where λ is the non-negative intensity vector, and an expression for describing a DMU (x_0, y_0) as follow:

$$x_0=X\lambda-s^-, y_0=Y\lambda+s^+$$

$s^-$is slack of input and represents excess of input, s^+ is slacks of output and represents shortage of output.

Tone (2001)’s SBM model is formulated as follows:

$$
\begin{aligned}
Minimize\,\rho = & \frac{1-(\frac{1}{m})\sum_{i=1}^{m}\frac{s^{-}{}_{i}}{x_{io}}}{1-(\frac{1}{s})\sum_{r=1}^{m}\frac{s_r^{+}}{y_{ro}}} \\
\text{s.t. } x_0 = & X\lambda + s^{-}, \\
y_0 = & Y\lambda - s^{+} \\
s^{+} \geq 0, & s^{-} \geq 0, \lambda \geq 0
\end{aligned}
\tag{3.1}
$$

Denominator of the objective function is the ratio of average efficiency improvement in input. It means that the ratio represents average amount of decreased m inputs. Numerator of the function is the ratio of average efficiency improvement in output. And it corresponds to average amount of increased s outputs.

Therefore minimize ρ makes the efficiency increased by the improvement of inputs and outputs at the same time. The constraints limit each DMUs that does not exist out of the production frontier.

3.1.2 The Directional SBM-DEA Model

We assume there are J decision-making units (DMUs) and each $DMU_j(J=1,\cdots,n)$ transforms inputs, $x_{ij}(i=1,\cdots,m)$, into outputs, $y_{rj}(r=1,\cdots,n)$. Further, observed quantities of inputs and outputs, x_{ij} and y_{rj}, are assumed to be positive.

The DEA production possibility set is denoted as:

$$P=\left\{(x,y)|x \geq X\lambda,\, y \leq Y\lambda,\, \sum\lambda = 1,\, \lambda \geq 0\right\}$$

The λ is intensity variables that form linear combinations of observed inputs and outputs with variable returns to scale imposed by the constraint that $\sum\lambda = 1$.

Directional SBM (slacks-based measure) is defined as:

$$
\begin{aligned}
\vec{S}(x_0, y_0; g^x, g^y) = \max & \frac{\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^x}{g_i^x} + \frac{1}{s}\sum_{r=1}^{s}\frac{s_r^y}{g_r^y}}{2} \\
x_{i0} = & \sum_{j=1}^{J} x_{ij}\lambda_j + s_i^x \\
y_{r0} = & \sum_{j=1}^{J} y_{rj}\lambda_j + s_r^y
\end{aligned}
\tag{3.2}
$$

Where the vector (x_0, y_0) indicates DMU_0's input and output vector and g^x, g^y are positive directional vectors that contract inputs and expand outputs. The directional vectors have the same units of measurement as the vectors of input and output slack, which allow the ratios of normalized slacks to be added, the objective maximizes the sum of average input inefficiency and average output inefficiency.

The directional SBM measure is related to the DEA directional technology distance function. Originally conceived by Luenberger as the shortage function in production theory and the benefit function in consumer theory, the directional technology distance function was adapted and further developed by Chambers et al.

It takes the following form:

$$\overrightarrow{D}(x_0, y_0; g^x, g^y) = \max_{\beta, z, t^x, t^y,} \left\{ \begin{array}{c} \beta : x_{i0} = \sum_{j=1}^{J} x_{ij} z_j + \beta g^{x_i} + t_i^x, \\ y_{ro} = \sum_{j=1}^{J} y_{rj} z_j - \beta g_r^y - t_r^y; \sum_{j=1}^{J} Z_j = 1; t_i^x, t_r^y, Z_j \geq 0, \beta free \end{array} \right\} \quad (3.3)$$

Where t_i^X and t_r^y represent the slack in the input and output constraints that remain once a firm has moved onto the frontier for the directional vectors g^x, g^y. This function seeks the maximum contraction in inputs and expansion in outputs that is feasible for the directional vectors g^x, g^y. However, when estimated using DEA, the directional distance function allows slack in the input and output constraints that decline the technology.

Let (β, z, t^X, t^y) solve the optimization problem (3.3) and define $s_i^X = \beta g_i^X + t_i^X$, $s_r^y = \beta g_r^y + t_r^y$, and $\lambda_j = Z_j$ .Then problem (3.2) can be rewritten as

$$\overrightarrow{S}(x_0, y_0; g^x, g^y) = \max_{\beta, z, t^X, t^y,} \beta + \frac{\frac{1}{m}\sum_{i=1}^{m} \frac{t_i^x}{g_i^x} + \frac{1}{s}\sum_{r=1}^{s} \frac{t_r^y}{g^{y_r}}}{2}$$

$$x_{i0} = \sum_{j=1}^{J} x_{ij}\lambda_j + \beta g_i^x + t_i^x,$$

$$y_{r0} = \sum_{j=1}^{J} y_{rj}\lambda_j - (\beta g_r^y + t_r^y),$$

$$\sum_{j=1}^{J} \lambda_j = 1$$

$$\beta g_i^x + t_i^x \geq 0, \beta g_r^y + t_r^y \geq 0, \lambda_j \geq 0$$

Clearly, we have $\overrightarrow{S}(x_0, y_0; g^x, g^y) \geq \beta = \overrightarrow{D}(x_0, y_0; g^x, g^y)$. Therefore, for DMU_0

with $(x_0, y_0) \in T$, directional SBI is no less than the DEA directional distance function and the two are equal when there are no slacks in the constraints defining the technology.

<Fig 2> illustrates the construction of $\vec{S}(x_0, y_0; g^x, g^y)$ and $\vec{D}(x_0, y_0; g^x, g^y)$. We observe four DMU_0 represented by points A, B, C and E. The DEA technology T, is the set of all inputs and outputs bounded by the line XAB and the horizontal extension from B. The Pareto-Koopmans' efficient subset is represented by the line AB, while the directional vector is represented by the ray OG. The DMUs C and E produce inside the frontier and are technically inefficient.

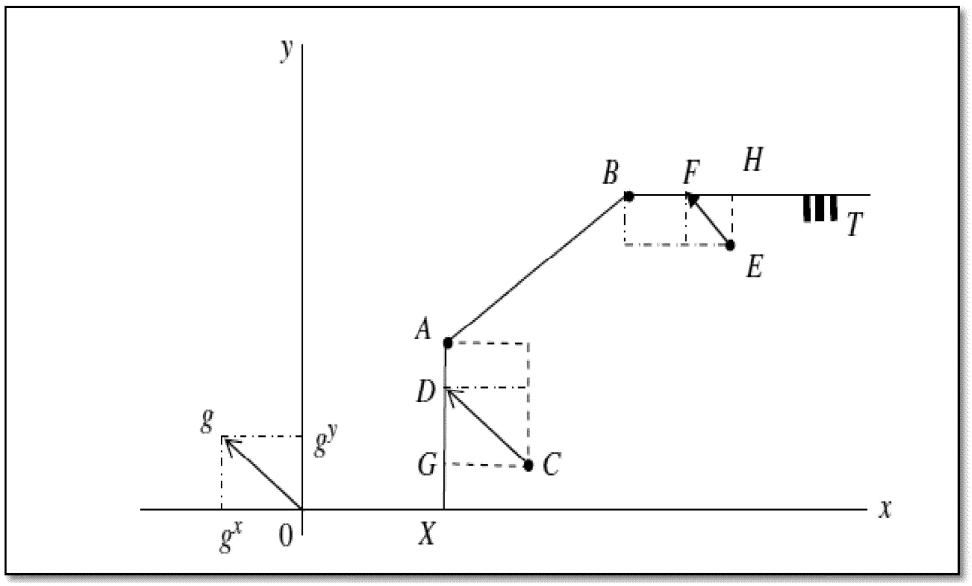

Fig 2.
Illustration of the Directional Distance Function and
Directional Slacks-based measure

When using the directional technology distance function DMU C has $\vec{D}(x_c, y_c; g^x, g^y) = CD/OG$. While DMU E has $\vec{D}(x_E, y_E; g^x, g^y) = EF/OG$ when using the directional SBI, DMUs C and E have, respectively, $\vec{S}(x_c, y_c; g^x, g^y) = \left(\frac{CD}{OG}\right) + \frac{1}{2}\left(\frac{AD}{g^y}\right)$ and $\vec{S}(x_E, y_E; g^x, g^y) = \left(\frac{EF}{OG}\right) + \frac{1}{2}\left(\frac{BF}{g^x}\right)$.

We define directional technical inefficiency bias as the difference between directional SBM and the directional technology distance function:

$$\overrightarrow{B}(x_{0,}\, y_0; g^x, g^y) = \overrightarrow{S}(x_{0,}\, y_0; g^x, g^y) - \overrightarrow{D}(x_{0,}\, y_0; g^x, g^y)$$

This bias arises when a DMU cannot further contract inputs and expand outputs given the directional vectors g^x and g^y, but slack in at least one input constraint or output constraint still exists. When $\overrightarrow{B}(x_{0,}\, y_0; g^x, g^y) = 0$, the DMU is evaluated relative to a point in the Pareto-Koopman's efficient subset of T. where there is no slack in the constraints defining the technology. Increasing values of $\overrightarrow{B}(x_{0,}\, y_0; g^x, g^y)$ indicate greater bias due to the existence of slack.

3.2 Data

In this research, we investigated the operational efficiency of major airlines in Asia-Pacific region. Therefore, as shown in <Table 2>,14 airlines from different parts of Asia-Pacific region were selected as the objectives of this research.

Table 2.
Asia-Pacific Airlines in Cluded in the Analysis

No	Airline	IATA Code	Country
1	Korean Air	KE	Korea
2	Asiana Airline	OZ	Korea
3	Air China	CA	China
4	China Eastern	MU	China
5	China Southern	CZ	China
6	Hainan Airlines	HU	China
7	China Airlines	CI	Taiwan
8	EVA Air	BR	Taiwan
9	Cathay Pacific	CX	Hong Kong
10	Japan Airlines	JL	Japan
11	All Nippon Airways	NH	Japan
12	Singapore Airlines	SQ	Singapore
13	Malaysia Airlines	MH	Malaysia
14	Thai Airways	TG	Thailand

To estimate the operational efficiency, we used balanced panel data on Asia-Pacific airline companies in the years from 2003-2011 (14 airline companies years=126 observations). These airlines are leading carriers in their respective countries or area. The data set was extracted from World Air Transport Statistics published by International Air Transport Association (IATA) and annual reports of the sample airlines.

The input factors are measured by three indicators:

(1) ASK (Available Seat Kilometers) captures the total flight passenger capacity of an airline in kilometers. It is obtained by multiplying the total number of seats available for scheduled passengers and total number of kilometers those seats were flown.

(2) ATK (Available Tonne Kilometers) is a measure of an airline's total capacity (both passenger and cargo). It is obtained by multiplying the capacity in tonnes and total number of kilometers those tonnes were flown.

(3) Labor is the amount of person who is employed by the airline.

The output factors will also be measured by three indicators: RPK (Revenue Passenger Kilometers), RTK (Revenue Tonne Kilometers), Sales.

(1) RPK (Revenue Passenger Kilometers) is a measure of the sales volume of passenger traffic. A passenger for whose transportation an air carrier receives commercial remuneration is called a revenue passenger. A revenue passenger-kilometer is flown when a revenue passenger is carried one kilometer. The RPK of an airline is the sum of the products obtained by multiplying the number of revenue passengers carried on each flight stage by stage distance. It is the total number of kilometers travelled by all passengers.

(2) RTK (Revenue Tonne Kilometers) is measure of utilized capacity for passengers and cargo expressed in metric tonnes, multiplied by the distance flown.

(3) Sales are the airline's income received from passenger and cargo transportation over the given period of time.

It clearly shows the mean value of ASK input was 70,623,575 (thousands of kilometers), ATK input was 12,947,686 (thousand tonnes of kilometers), and that of Labor input was 18,992(person). The RPK output was 52,075,136 (thousand persons of kilometers), RTK (thousand tonnes of kilometers), whereas the outputs of sales were 7,040 (million dollar).

Table 3.
Descriptive Statistics of Input and Output Variables (2003-2011)

Variable	Unit	Mean	Max	Min	Std.dev
Inputs					
ASK	10^3-km	70,623,575	150,557,972	14,153,260	32,631,125
ATK	10^3ton-km	12,947,686	24,647,217	1,568,593	5,714,111
Labor	Person	18,992	71,696	4,455	12,811
Outputs					
RPK	10^3person- km	52,075,136	121,943,817	9,828,880	24,636,770
RTK	10^3ton-km	8,754,740	18,226,494	1,052,086	4,051,866
Sales	million Dollar	6,957	20,113	1,564	4,974

<Table 4> shows the correlation matrix of inputs and outputs. We can see that labor has low correlation with RTK, ATK and Sales. This is because that the most of the airline employee work related with the passengers and few of them are worked with cargo transportation. So the labor doesn't have much correlation with cargo variables ATK, RTK. Besides the cargo transportation has a strong correlation with the airline sales. This is the reason why the labor also has low correlation with the Sales.

Table 4.
Correlation Matrix of Input and Output Variables

	ASK	ATK	Labor	RPK	RTK	Sales
ASK	1.00					
ATK	0.84	1.00				
Labor	0.80	0.23	1.00			
RPK	0.98	0.85	0.56	1.00		
RTK	0.73	0.95	0.20	0.79	1.00	
Sales	0.81	0.72	0.18	0.75	0.75	1.00

4. Estimation Results

4.1 Results of the Basic DEA Model

In this part, we used an input-oriented, technically efficient (TE) DEA index, assuming that airlines aim to minimize the inputs resulting from their activities.

The results of basic data envelopment analysis for the major Asia-Pacific airlines efficiency are presented in <Table 5> and ranked according to the CCR model, using R software. In order to estimate the average performance of an airline during the study period, we also calculated the average efficiency scores by taking values of each input or output variable as annual mean value respectively.

We ranked the efficiency score by CCR model for two reasons. On the one hand, under DEA, they have to be computed anyway in order to measure scale efficiencies. On the other hand, we are interested in estimating the potential bias implied by the computation of DEA-CRS technical efficiency scores when the true technology is characterized by variable return to scale. The score of efficiency ranges from 0 to 1. An airline with the score of one is relatively efficient. Otherwise, one with a score of less than 1 is relatively inefficient.

The results of <Table 5> can be explained as follows. First, there are some significant differences in efficiency scores among the airlines. From 2003-2011, most of the airlines get a high efficiency score. Especially, the mean CCR, BCC, Scale efficiency scores of Cathay Pacific, Japan Airlines, Singapore Airlines are 1. It indicates that these three airlines operated efficiently in the given period and should be regard as the benchmarking airlines. Also we should mention that although the efficiency scores of Hainan Airline and EVA Airline are 1, these two airlines are relatively smaller in scale than others. So they should not be considered as the good benchmarking airline. Besides the mean efficiency scores of Korean Air, Asiana Airlines, All Nippon Airlines are almost 1. This means that these airlines operated at a high level of efficiency, so these airlines also could be regarded as the benchmarking airlines. Compared to these airlines, we can know that the rest of the airlines are relatively inefficient.

Second, all CRS technically efficient airlines are also technically efficient in VRS, which means that the dominant source of efficiency is scale. However, the airlines which are not efficient in CCR model got a higher efficiency score in BCC model, such as Air China, China Southern, Malaysia Airlines, and Thai Airways. This is reasonable since the piecewise linear frontier that allows for variable returns to scale in BCC model envelopes the observation more tightly. The rationale for interpreting BCC as management skills is

based on the contrast between the CCR and BCC models. The CCR model identifies the overall inefficiency, whereas BCC differentiates between technical efficiency and scale efficiency. Based on this differentiation, the ratio between CCR and BCC enables the estimation of scale efficiency in <Table 5> and, assuming efficiency is due to managerial skills and scale, the BCC scores are thus interpreted as managerial skills.

Third, in terms of scale efficiency, the scale efficiency results are rather similar to the CCR technical efficiency. In fact, those airlines that score CCR technical efficiency of 1 also produce an identical scale efficiency score. However some airlines such as Air China, China Eastern, China Airline, and Malaysia Airline don't operate at a high level of technical efficiency, but they get al high score in scale efficiency. This suggests that, although these airlines are not operated efficiently, they properly used the optimal size of scale in operation.

Table 5.
Asia-Pacific Airlines Efficiency Scores, 2003-2010

No.	Airlines	2003	2004	2005	2006	2007	2008	2009	2010	2011	Average scores-CCR	Average scores-BCC	Scale Efficiency
1	Korean Air	0.967	1.000	1.000	1.000	1.000	1.000	0.996	0.972	0.984	0.991	1.000	0.991
2	Asiana Airlines	0.969	0.989	1.000	1.000	1.000	1.000	0.969	1.000	1.000	0.992	1.000	0.992
3	Air China	0.915	0.958	0.913	0.973	0.976	0.962	0.990	1.000	1.000	0.965	0.982	0.983
4	China Eastern	0.848	0.884	0.837	0.921	0.913	0.908	0.927	1.000	0.989	0.914	0.936	0.977
5	China Southern	0.917	0.928	0.898	0.935	0.926	0.944	0.979	0.966	0.965	0.940	0.993	0.946
6	Hainan Airlines	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
7	China Airlines	0.966	1.000	0.972	0.968	0.953	0.976	1.000	1.000	0.994	0.981	0.993	0.988
8	EVA Air	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
9	Cathay Pacific	0.999	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
10	Japan Airlines	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
11	All Nippon Airways	1.000	1.000	1.000	1.000	0.960	1.000	1.000	1.000	0.946	0.990	0.991	0.998
12	Singapore Airlines	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
13	Malaysia Airlines	0.937	0.914	0.863	0.909	0.925	0.997	1.000	1.000	0.997	0.949	0.960	0.988
14	Thai Airways	0.989	0.973	0.892	0.996	0.982	0.951	0.933	0.924	0.871	0.946	0.972	0.973
Mean		0.965	0.975	0.955	0.979	0.974	0.981	0.985	0.990	0.982	0.976	0.988	0.988
Median		0.979	1.000	1.000	1.000	0.991	1.000	1.000	1.000	0.999	0.990	0.996	0.992
Std.dev		0.046	0.039	0.061	0.033	0.033	0.029	0.025	0.022	0.036	0.028	0.019	0.015

Table 6.
Average Efficiency Scores of Asia-Pacific Area Airlines

	2003	2004	2005	2006	2007	2008	2009	2010	2011
TE	0.965	0.975	0.955	0.979	0.974	0.981	0.985	0.990	0.982
PTE	0.974	0.986	0.975	0.995	0.985	0.995	0.991	0.996	0.992
SE	0.991	0.989	0.980	0.983	0.989	0.986	0.994	0.995	0.989

Average Efficiency Scores of Asia-Pacific Area Airlines

In general, scale efficiencies among all the airlines remain consistently high above 0.98. This suggests that the Asia Pacific airlines are apt in adjusting its scale of operations with minimal impact on its corresponding production function.

Furthermore, the time-series patterns of TE (Technical Efficiency), PTE (Pure Technical Efficiency) and SE (Scale Efficiency) under the DEA analysis can be measured. <Table 6> shows the mean technical efficiency, pure technical efficiency and scale efficiency of the samples of Asia-Pacific Airlines from 2003 to 2011.

As can be seen from the table, when the sample Asia-Pacific airlines are taken as a whole, both TE and SE have shown an upward trend. On the other hand, PTE has exhibited a fair amount of fluctuation over time with no noticeable upward trend observed, suggesting that more efforts are needed to improve PTE. We can found that the mean technical efficiency score of 14 Asia-Pacific airlines are close to 0.976, which means that most airlines are close to being efficient. And the efficiency scores between 2004 and 2005 sharply declined due to break out of SARS and Southeast Asia earthquake and tsunami that had a severe negative impact on air travel demand. After that, the operational efficiency score went straight up quickly. We also notice that the efficiency score declined from 2010, this is due to the substantial fuel price rise and global economic downturn.

4.2 Results of the SBM-DEA Model

In this section, we present and discuss the results of the application of a non-radial, slacks based measure (SBM) of efficiency. The original SBM DEA model computes the ratio of the average inputs reduction to the average output increase. Minimizing that ratio implies the simultaneous pursuit of improvements in both inputs and outputs. It is, therefore, the SBM efficiency score leaves no input or output slack unaccounted and all possible improvements are exhausted and properly taken into account in the objective function.

The results are presented in <Table 7>. Overall, we see that all the efficiency scores are much lower than the CCR models. And most of the inefficient airlines show very low efficiency scores when using the SBM-DEA model. With regard to the operational efficiency, the airlines that get the highest efficiency score are only Singapore Airlines and Japan Airlines. The lowest one is China Eastern which efficiency score is 0.648.

Also we can find that the airlines from the same country show smaller difference in the average efficiency. Most of the airlines from Korea and Japan have a high level of operational efficiency while China and Southeast Asia airlines are not performed efficiently. The finding indicates that we can analyze the airlines operational efficiency difference divided by region. And this issue will be discussed in the next section.

4.3 Results of Directional SBM-DEA Model

To measure the Airline efficiency more accurately, we used the directional slacks based measure (SBM) model. Also variable returns to scales (VRS) have been assumed. Since given the limited competition among the airlines, it cannot be expected that they operate at the most productive scale size.

From the result as showed in <Table 8>, we can see that, from 2003-2011, Korean Air, Asiana Airline, Cathay Pacific, Japan Airlines, Singapore Airlines operate efficiently with an average score of 1. So these airlines could be the benchmarking airlines for other Asia-Pacific airlines.

To find the factors that influence operational efficiency, we should further look into slack values of all the input and output variables. The results are presented in <Table 9>. It is found that low-ranking inefficient airlines have extremely high slack values in input and output variables. For example, Malaysia Airlines, show that it has average excess values of 23.51% in Labor as well as average shortage values of 7.95%, 4.36% in RTK and Sales. All of the airlines in China have so much waste in labor while handling too insufficient RTK or Sales.

For the inefficient airlines, the average excess values of 2.96%, 1.46%, 17.08% in ASK, ATK, Labor and average shortage values of 0.71%, 6.12%, 7.24% in RPK, RTK and Sales. It suggests that they use massive input resources in order to produce more outputs. The excess of labor is the major factor cause the airline operational inefficiency,

Table 7.
Asia-Pacific Airlines SBM Efficiency Scores (2003-2011)

Airlines	2003	2004	2005	2006	2007	2008	2009	2010	2011	Average
Korean Air	0.698	1.000	1.000	1.000	1.000	1.000	0.872	0.854	0.924	0.928
Asiana Airlines	0.815	0.893	1.000	1.000	1.000	1.000	0.809	1.000	1.000	0.946
Air China	0.499	0.735	0.702	0.868	0.839	0.876	0.910	1.000	1.000	0.825
China Eastern	0.484	0.515	0.513	0.628	0.624	0.637	0.658	1.000	0.773	0.648
China Southern	0.494	0.537	0.691	0.712	0.696	0.788	0.822	0.755	0.742	0.693
Hainan Airlines	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
China Airlines	0.787	1.000	0.828	0.842	0.830	0.840	1.000	1.000	0.863	0.888
EVA Air	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Cathay Pacific	0.828	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.981
Japan Airlines	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
All Nippon Airways	1.000	1.000	1.000	1.000	0.809	1.000	1.000	1.000	0.837	0.961
Singapore Airlines	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Malaysia Airlines	0.506	0.594	0.595	0.716	0.713	0.850	1.000	1.000	0.854	0.759
Thai Airways	0.797	0.756	0.612	0.831	0.752	0.718	0.614	0.544	0.452	0.675

Table 8.
Asia-Pacific Airlines Directional-SBM Efficiency Scores (2003-2011)

Airlines	2003	2004	2005	2006	2007	2008	2009	2010	2011	Average
Korean Air	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Asiana Airlines	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Air China	0.833	0.946	0.891	0.983	1.000	1.000	0.942	1.000	1.000	0.955
China Eastern	0.857	0.865	0.822	0.878	0.894	0.873	0.865	1.000	0.892	0.883
China Southern	0.798	1.000	1.000	1.000	1.000	1.000	0.966	1.000	1.000	0.974
Hainan Airlines	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
China Airlines	0.921	1.000	1.000	0.937	1.000	1.000	0.976	1.000	0.936	0.974
EVA Air	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Cathay Pacific	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Japan Airlines	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
All Nippon Airways	1.000	1.000	1.000	1.000	0.911	1.000	0.985	1.000	1.000	0.988
Singapore Airlines	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Malaysia Airlines	0.786	0.918	0.855	0.901	0.903	1.000	0.894	1.000	0.929	0.910
Thai Airways	1.000	1.000	0.914	1.000	1.000	1.000	0.986	0.835	0.786	0.947

Table 9.
Summary of Average Excess in Inputs and Shortagein Outputs

Airlines	Excess of ASK	Excess of ATK	Excess of Labor	Shortage of RPK	Shortage of RTK	Shortage of Sales
Korean Air	0	0	0	0	0	0
Asiana Airlines	0.07%	0	2.86%	0.71%	0	0
Air China	2.62%	1.71%	12.16%	0	6.17%	0.45%
China Eastern	8.96%	3.05%	48.02%	0.05%	9.18%	0
China Southern	0.96%	0	4.47%	0	3.06%	4.94%
Hainan Airlines	0	0	0	0	0	0
China Airlines	0.42%	1.78%	12.32%	1.30%	0	3.08%
EVA Air	0	0	0	0	0	0
Cathay Pacific	0	0	0	0	0	0
Japan Airlines	0	0	0	0	0	0
All Nippon Airways	0.41%	0.94%	0.56%	0	4.04%	0
Singapore Airlines	0	0	0	0	0	0
Malaysia Airlines	4.91%	0.23%	23.51%	0.76%	7.95%	4.36%
Thai Airways	5.33%	1.08%	15.68%	0	6.34%	23.35%

4.4 Discussions

4.4.1 Efficiency Score Difference among DEA Models

As we mentioned above, we used various DEA models to estimate the operational efficiency of Asia-Pacific Airlines. So it is essential to examine the difference between different DEA models.

With regard to the results of different DEA models, we can find that the efficiency score of SBM-DEA model is lower than the score of traditional DEA models, indicating that without considering input and output slacks, the traditional DEA models overestimates the real efficiency score. Also under the condition of variable return to scale, the efficiency score is higher than under the condition of constant returns to scale.

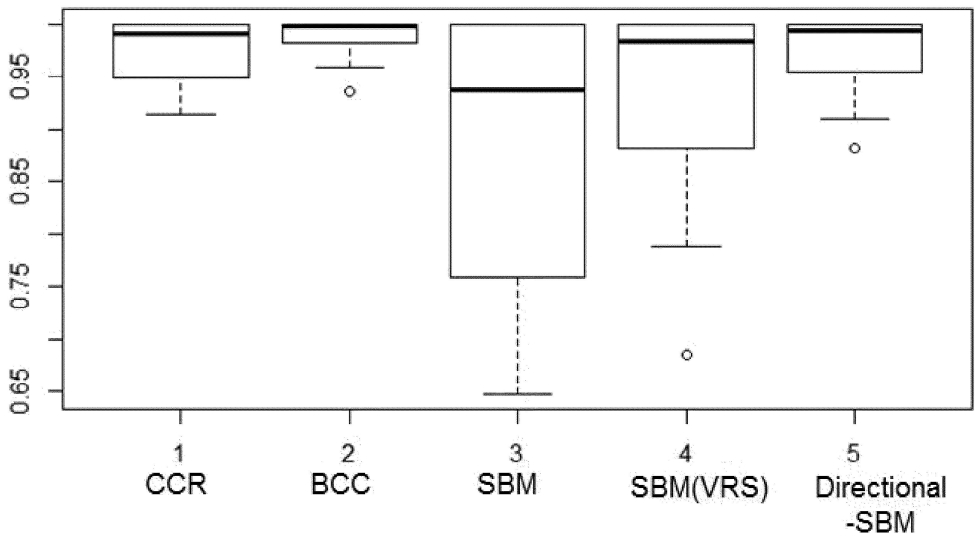

Fig 3.
Boxplots of Different DEA Models

4.4.2 Efficiency Score Difference among Countries

According to the results of the Asia-Pacific airlines operational efficiency performances, we can find that the airlines that from the same country show smaller difference in the efficiency score. Based on this finding, we analysed the efficiency trend of between different countries in Asia-Pacific region during 2003-2011.

Table 10.
Average Technical Efficiency Scores of Korea, China, Japan, ASEAN Airlines

	2003	2004	2005	2006	2007	2008	2009	2010	2011
ROK	0.968	0.995	1.000	1.000	1.000	1.000	0.983	0.986	0.992
CHN	0.893	0.923	0.883	0.943	0.938	0.938	0.965	0.989	0.985
JPN	1.000	1.000	1.000	1.000	0.980	1.000	1.000	1.000	0.973
ASEAN	0.954	0.973	0.961	0.981	0.973	0.979	0.983	0.992	0.983

Table 11.
Average SBM Efficiency Scores of Korea, China, Japan, ASEAN Airlines

	2003	2004	2005	2006	2007	2008	2009	2010	2011
ROK	0.757	0.947	1.000	1.000	1.000	1.000	0.841	0.927	0.962
CHN	0.492	0.596	0.635	0.736	0.720	0.767	0.797	0.918	0.838
JPN	1.000	1.000	1.000	1.000	0.905	1.000	1.000	1.000	0.919
ASEAN	0.750	0.847	0.878	0.912	0.875	0.922	0.879	0.948	0.906

Table 12.
Average Scale Efficiency Scores of Korea, China, Japan, ASEAN Airlines

	2003	2004	2005	2006	2007	2008	2009	2010	2011
ROK	0.968	0.995	1.000	1.000	1.000	1.000	0.984	0.986	0.992
CHN	0.985	0.969	0.943	0.945	0.956	0.961	0.986	0.989	0.985
JPN	1.000	1.000	1.000	1.000	0.999	1.000	1.000	1.000	0.973
ASEAN	0.995	0.982	0.964	0.984	0.994	0.983	0.996	0.995	0.990

The results demonstrate that the regional operational efficiency is different among four regions. Although the SBM efficiency scores are much lower than the technical efficiency scores, we can come to the same conclusion that the airlines of Japan showed the best operational efficiency, followed by airlines of Korea. The airlines from the ASEAN ranked the third. In general, the efficient airlines are located in the Northeast Asian region, resulting in the higher efficient scores during the research period. The ASEAN airlines

appear less efficient than the Northeast Asian airlines.

The airlines of China show the worst operational efficiency at the 2003. But, as years went by, the airlines of China operate more and more efficiently and the gaps with other regions are narrowed.

As is shown in <Table 12>, we can see some sudden decrease or increase happened in scale efficiency. We found that China and ASEAN have a sharp scale efficiency decline during 2003-2005. This is influenced by the break out of SARS and the Southeast Asian tsunami. The scale efficiency has gradually increased since 2006. And China has a steady increase since 2008 owing to the opening of Beijing Olympics Games, which has a positive effect on the air travel demand. Also Japan always has a high scale efficiency score but drop sharply in 2010 due to the earthquake accompanied with the nuclear pollution, which has a bad influence on airline operational performance.

5. Concluding Remarks

Nowadays transport industries have become increasingly important in the global economy. Issues in the aviation industry are especially important for a large, free market economy like the Asia-Pacific region, because they can influence both global and regional economic development and international politics.

Although the efficiency of the aviation industry has been widely discussed in previous literature, there are still some important points need to be further researched. This paper employs basic DEA methods and non-radial slacks-based measures to analyze the operational efficiency of Asia-Pacific region. The concept of directional SBM-DEA has been applied infrequently in previous studies of the aviation industry. Therefore, this paper aimed to establish a directional SBM- DEA to measure operational efficiency, to discuss influencing factors and to evaluate the benchmarking airlines from a more complete viewpoint. For this purpose, 14 major Asia-Pacific airlines were chosen with regard to ASK, ATK, Labor as the input variables, RPK, RTK, Sales as the output variables.

The main findings, as well as the policy implications of the research can briefly be described as follows;

First, the airlines of Korea and Japan are operated efficiently and could be the benchmarking of other airlines.

Second, inputs are major causes of the airlines' inefficiency. Most of the airlines in China and Southeast Asia are not efficient. According to the result of the directional SBM-DEA, the reason could be the much excess of labor in operation. Thus, the promotion

of flexible labor policies to reduce the excess labor and improving the operational efficiency should be implemented in the future.

Third, large gaps in both pure efficiency and scale efficiency exist at the regional level of economic development. Most of the developed country has a high operational efficiency, while the developing countries suffer from poor operational efficiency. Thus, there is considerable room for improvement.

And some special event such as earthquake, disease could have a positive/negative effect on the operational efficiency.

This study contributes to the current body of relevant literature by exploring the feasible application of the SBM-DEA approach for airline operational efficiency in Asia-Pacific. However, some caveats should be taken in interpreting the results of this study.

First, the efficiency study have not considered the undesirable outputs that airline generate, for instance, emissions. Therefore, it is important to carry out a research on the efficiency of airlines from an environmental perspective. However, it is different and complex to calculate exactly how much emission from each airline in the years 2003-2010. So the research to evaluate more meaningful environmental efficiency with emissions has left for future tasks.

Second, it is noted that the results of DEA techniques show relative efficiency depending on the collected sample rather than absolute one. This stems from the fact that all efficiency estimations of decision-making units are affected by how we collect the sample of the DMUs since the efficient frontier line is drawn from the given sample. The analyzed efficiencies in this study are the relative efficiencies among decision making units only in Asia-Pacific airlines. There is a possibility that the efficient airlines can be regarded as inefficient airlines if they are compared with other regional major airlines. Thus, it is necessary to extend numbers of observed airlines to the world-wide scope in the future research.

References

Banker, R. D., Charnes, A., Cooper, W. W., Some models for estimating technical and scale inefficiencies is data envelopment analysis, *Management Science* 30, 1984, pp. 1078-1092.

Barbot, C., Costa, A., and Sochirca, E., Airlines performance in the new market context: A comparative productivity and efficiency analysis, *Journal of Air Transport Management, vol.14, 2008, pp. 270-274.*

Carlos, P.B., The technical efficiency of US airlines, *Transportation Research Part A,*vol.50, 2013, pp. 139-148.

Carlos, P. B., An evaluation of European airlines' operational performance, *Production Economics*, vol.122, 2009, pp. 525-533.

Charnes, A., Cooper, W. W., and Rhodes, E., Measuring the efficiency of decision making units, *European Journal of Operation Research*, vol.2, issue 6, 1978, pp. 429-444.

Cristina, B., Alvaro. C., and Elena. S., Airlines performance in the new market context: A comparative productivity and efficiency analysis, *Journal of Air Transport Management*, vol.14, 2008, pp. 270-274.

Fang,T. S., Lee.,T. S., A slacks-based measure of super-efficiency in data envelopment analysis: An alternative approach, *Omega*, vol. 41, 2013, pp. 731-734

Fukuyama, H., Webber, W.L.,A directional slacks-based measure of technical inefficiency. *Socio-Economic Planning Science*, vol.43, 2009, pp. 274-287.

George. A., Alexander. J., European vs. U.S. airlines: Performance comparison in a dynamic market, *Tourism Management*, vol.33, 2012, pp. 317-326.

Ha,H. K., Yoshida, Y., and Zhang, A., "Comparative Analysis of Efficiency for Major Northeast Asia Airports", *Transportation Journal*, vol. 49, 2010, pp.9-23.

Hoff, A., Second stage DEA: Comparison of approaches for modeling the DEA score, *European Journal of Operational Research*, vol.181, 2006, pp. 425-435.

Lee, J. Y., Hyun, K., Airline Networks in East Asia, *Journal of International Logistics and Trade*, vol. 12(3), 2014, pp.21~37.

Ohash,H., Kim, T. S., Choice of air cargo transshipment airport: an application to air cargo traffic to/from Northeast Asia, *Journal of Air Transport Management*,vol.11, issue 3, 2005, pp. 149-159.

Park, A.R., Ha, H. K., Comparative Analysis of Methodologies to Evaluate Air Cargo Carriers' Service Quality" Focusing on SEVQUAL and SERVPERF, *Journal of International Logistics and Trade*, vol. 11(2), 2013, pp.29~46.

Rico. M., David. A.H., The impact of strategic management and fleet planning on airline efficiency- A random effects Tobit model based on DEA efficiency scores, *Transportation Research Part A*, vol. 45, 2011, pp. 686-695.

Rolf. F., Shawna. G., Directional distance functions and slacks-based measures of efficiency, *European Journal of Operational Research*, vol. 200, 2010, pp. 320-322.

Sebastián. L., Ester. G., Slacks-based measure of efficiency of airports with airlines delays as undesirable outputs, *Contents & Operations Research*, vol.38, 2011, pp. 131-139

Shao. W. L., Joyce. M. W. L., Loon. C. T., Operational efficiencies across Asia Pacific airports, *Transportation Research Part E*, vol. 45, 2009, pp. 654-665.

Tone,K., A slacks-base measure of efficiency in data envelopment analysis", *European Journal of Operational Research*, 130, pp. 498-509.

Wu,Y. Q., He,C. Z., and Cao,X. F., The impact of environmental variables on the efficiency of Chinese and other non-Chinese airlines, *Journal of Air Transport Management*, vol. 29, 2013, pp. 35-38.