경영학석사 학위논문

The Measurement of Efficiency of Asia-Pacific Airports: An application of Network Data Envelopment Analysis

2단계 네트워크 **DEA**를 이용한 아태 지역 주요 공항 성과 분석

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Abstract

This paper aims to analyze the efficiency level of airport in Asia-Pacific region, as airport industry plays a significant role for exchange of human and material resources. By using two-stage network DEA, efficiency of the airport is decomposed into two sub-procedures, operations and revenue efficiency, in order to better understand the efficiency process of the airports. In addition to the efficiency evaluation, regression and non-parametric statistical testing were performed to test research questions regarding what internal and external factors determine the difference in efficiency level among the airports. It was shown that Asia-Pacific airports have low efficiency especially in revenue-generating stage, leading to low overall efficiency. The market share of LCC did not have significant impact on the airport efficiency in this region. Also, several statistically significant factors were identified in terms of determining airport efficiency levels, providing implications for airports in terms of setting managerial strategies.

Keyword: **DEA, efficiency, airport performance, Asia-Pacific region, two-stage network DEA**

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1. Introduction

Aviation industry has emerged as a means of logistics and transportation, hand in hand with world economic development. Airport, as an intermediate between the aircraft and passengers, plays a significant role in exchange of human and material resources. Airport Council International (ACI) has forecasted the throughput of world airports to increase from 5 billion in 2010 to 10 billion in 2027 (ACI Global Traffic forecast, 2008). While airports were traditionally focused more on being public with universal service provision, recent move of airport competition intensification has brought about much change within and around airport industry, such as servitization and capital investments.

The recent growth of aviation industry in Asia-Pacific region is receiving noticeable attention. ACI has predicted Asia-Pacific region to become the biggest market, outrunning the European and American market. This rapid advance is due to the development of the emerging economy, along with population growth of the continent. Also, Open Skies Treaty, an agreement eliminating government interference in the commercial decisions of air carriers about routes, capacity, and pricing, freeing carriers, has been made amongst various countries to provide more affordable, convenient, and efficient air service for consumers (MOFA). By allowing air carriers unlimited market access to markets and the right to fly to all points, Open Skies agreements provide maximum operational flexibility for airline alliances. Hand-in-hand with this airline liberalization, Low-Cost Carriers (LCC), which was being operated mainly in Europe and America, is getting bigger chances to grow in Asia-Pacific region as well.

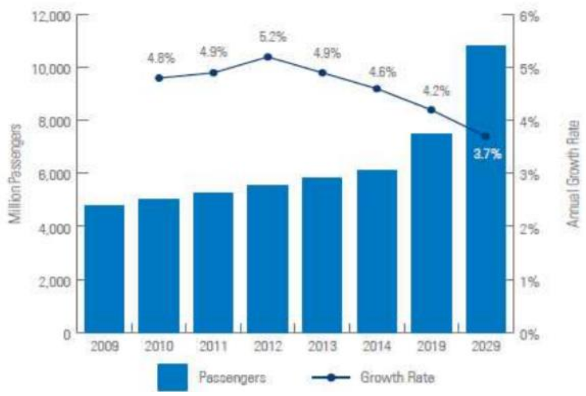


Figure 1 World passenger throughput forecast

LCC owns numerous definitions, but the general definition is an airline that is operated with an especially high emphasis on minimizing operating costs and without some of the traditional services and amenities provided in the fare, resulting in lower fares and fewer comforts. According to International Civil Aviation Organization (ICAO), Low-Cost Carriers have played a major role in this extraordinary expansion of aviation over the past quarter century, and there is every expectation that they will continue to do so. Low-cost carriers carried 984 million passengers in 2015, which was 28 percent of the world total scheduled passengers. This marked a 10 percent increase compared to 2014, which means Low-Cost Carriers experienced a passenger growth rate that was about one and a half times the rate of the world total average passenger growth. In comparison the Full-Service Carriers (FSC), LCCs take 18 percent of the airline market share (MOLIT),

With this trend of aviation growth, airport performance measurement has attracted much attention. Airports contribute to regional and national economic development as well as provide public goods and services in aiding national defense (Vasigh and Hamzaee, 1998), thus continuously measuring the performance and efficiency of airports has significant importance. It was shown that airlines choose airports that are more efficient, (Sarkis et al, 2000) and that 1% increase in efficiency of the airports would equate savings of at least $200 million for the US airlines, inferring the importance of efficiency management for airports (Jenkins, 1999). Also, airports should be efficient in order to be viewed as mature firms able to stand on their own (Gillen and Lall, 1997).

With the paradigm shift in Asia-Pacific airport industry, it is necessary to investigate the factors that affect the airport efficiency level. Thus, this paper analyzes the efficiency of Asia-Pacific airports, decomposing it into two sub-procedures. With further contemplation, this study aims to examine the relationship between several internal/external factors and airport efficiency. By doing so, the paper wishes to provide guidelines and suggestions for airports with relatively low efficiency score, and to serve as a reference material for domestic airports in the future.

This paper is organized as follows. In section 2, the literature related to this study is reviewed. Section 3 shows the research model and hypotheses, and how they are developed. Section 4 shows methodology and how they are measured. Section 5 presents the paper's results and section 6 shows the implication of the research. Lastly, this paper ends with section 7, which shows the limitation of the paper and suggestions for future research.

2. Literature review

2.1 Airport evaluation with the application of DEA

Efficiency refers to the ratio of output performance to input resources, and when an organization's efficiency is relatively high, it either means that it has invested the same amount of resources as others and gained higher output, or that it has spent less input to gain the same amount of output as others. Data Envelopment Analysis (DEA) has been widely used as a method to measure organizations' efficiency, along with TFP (Total Factor Productivity) and SFA (Stochastic Frontier Analysis). In the field of airport industry, with DEA, Gillen and Lall (1997) have analyzed 21 American airports from 1989 until 1993. Sarkis (2000) has analyzed the operations efficiency of 44 American airports in the period of 1990 until 1994. Adler et al (2001) evaluated the relative efficiency and quality of airports in West Europe, North America and Asia in 1996. Pels et al (2003) revealed that European airports in general were managed inefficiently, and Barros and Dieke (2007) measured efficiency level of 31 Italian airports in the period of 2001 and 2003. In domestic research field, H. Kim et al (2002) measured the efficiency of 16 domestic airports. D. Kim et al (2003) analyzed the airside efficiency of Incheon International airports, and H. Kim et al (2007) further measured efficiency of 14 domestic airports. By this method, studies could successfully analyze the efficiency of airports, but were limited to comparing relative efficiency of airports for a certain period or a specific point in time.

One of the criticisms DEA has received is that it only comes up with one efficiency score for the subject it aims to analyze, with the consideration of initial input and final output only. This may overlook the complex process that takes place within the organization, thus regarding the organization as a ‘black box’. To solve this limitation, network DEA started to further study the inner efficiency of organizations, through decomposing the process and calculating the efficiency score for each processes. Yu (2010) has analyzed Taiwan airports efficiency, dividing it into airside service process and landside service process. Lozano et al (2013) decomposed the Spain airport efficiency into aircraft movement process and aircraft loading process, and proved that Network DEA can more specifically pinpoint inefficiency than single process DEA. Maghbouli et al (2014) has also analyzed the efficiency level of Spain airports, looking at it into aircraft movement process and aircraft loading process, including undesirable variables. Liu (2016) analyzed 10 airports in East Asia, decomposing the efficiency process into aeronautical service sub-process and commercial service sub-process. S. Yoo et al (2017) analyzed 59 airports around the world, looking at the process as operations efficiency and revenue efficiency.

Factors leading to variation in the efficacy of an airport may not be understood using the DEA analysis (Gillen and Lall, 1997). Thus, recent movement is to combine DEA model and regression, as an approach to determine factors that affect the levels of efficiency in an airport company. Table 1 presents studies that has calculated efficiency levels, and then examined the determinant factors. However, many of the researchers only identified the determinants of the overall efficiency rather than the efficiencies of the sub-processes.

Table 1 Literature on airport efficiency using DEA and regression analysis

Author	Year	Object of the study	Factor	Results
Bazargan and Vasigh	2003	45 US commercial airports	Airport size	(-)
Adler et al	2013	85 European local airports	Grouping status	(-)
Barros and Sampaio	2004	1990~2000 Portuguese airports	airport size, location, government involvement	(+)
			Management structure	X
Lin and Hong	2006	20 world airports	Airport size, ownership	X
			hub status, location	(+)
S. Yoo et al	2017	59 world airports	Location, airport size	(+)
			Listing status, grouping status	X
Chi-Lok and Zhang	2009	25 Chinese airports	Listing status, open skies agreement, grouping status	(+)
Ha et al.	2013	12 East Asia arports	Airport competition	(+)
			Open skies agreement	X
Merkert R, Mangia L	2014	35 Italian airports and 46 Norwegian airports	Airport competition, military purpose, airport size	(+)
Tsui et al	2014	21 Asia-Pacific airports	International passengers %	(-)
			GDP per capita	(+)

(+): positive impact, (-): negative impact, X: no significant impact

Only a very limited number of studies investigated the relationship between LCC and airport efficiency. While numerous studies have been conducted on the effects of LCCs on air fares, passenger traffic and competition, there is limited amount of literature of the effects of LCC on airport operations and performance (Graham, 2013), and the geographic coverage of such studies are limited mostly to Europe (Choo and Oum, 2013). Furthermore, the empirical findings on the effects of LCCs on efficiency are inconclusive. While Bottasso et al (2012) and Coto Millan et al (2014) asserted LCC positively affect airport efficiency, Choo and Oum (2013) stated specialization in either LCC or FSC leads to higher efficiency.

Through the literature review, it was clear that DEA is widely applied in airport performance measurement, and that Network DEA was recently introduced to analyze the efficiency more elaborately. Also, additional regression analysis could bring about more meaningful findings. However, many studies only conducted regression on total efficiency score, and conclusions on whether the size or ownership of airports affects the efficiency level are indefinite. Moreover, market share of LCC in Asia-Pacific region is continuously increasing, but few studies have examined how it affects the airports' performance or efficiency level.

2.2 Data Envelopment Analysis

Data Envelopment Analysis or DEA is a linear programming technique that measure technical efficiency in a range of industries (Cooper, Seiford and Tone, 2000). It is a non-parametric technique that estimates the maximum potential output for a given set of inputs, primarily used to estimate efficiency. DEA was first introduced by Farrell (1957) as a linear programming method to measure efficiencies of organizations or institutions, which are called as DMUs (Decision Making Units). By doing this, one can set a best-practice benchmark, and form an empirical efficiency frontier. This was later further developed by Charnes, Cooper and Rhodes (1978), who included multiple set of inputs and outputs to the analysis model. Unlike other methodologies such as TFP (Total Factor Productivity) and SFA (Stochastic Frontier Analysis), DEA does not assume a certain production function. This makes DEA widely used in various organizations such as public sector, hospital and service organizations, as many times it is difficult to set a certain function among input and output variables.

There are largely two concepts in DEA method; CRS and VRS. CRS reflects the fact that output will change by the same proportion as inputs are changed (e.g. a doubling of all inputs will double output); VRS reflects the fact that production technology may exhibit increasing, constant and decreasing returns to scale. The effect of the scale assumption on the measure of capacity utilization is demonstrated in Figure 2.

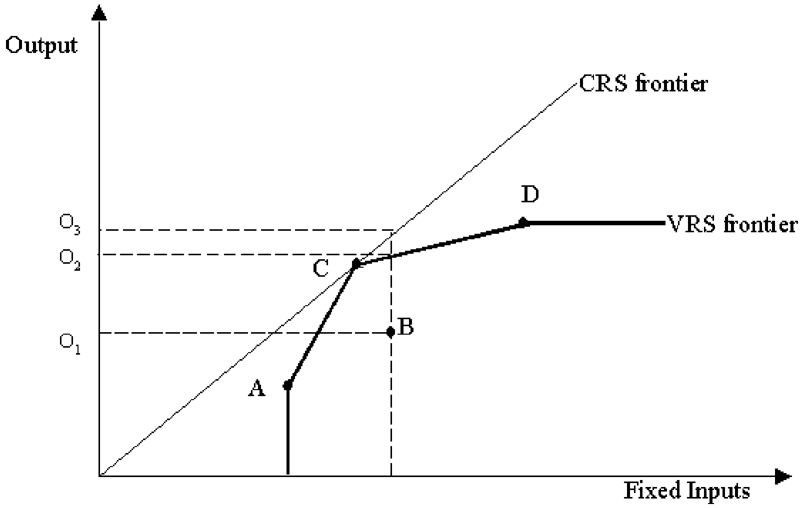


Figure 2 CRS and VRS frontiers

As mentioned in the previous section of literature review, recently, more studies are focusing on the internal process of DMUs, primarily through network DEA. One of the widely used methodologies is two stage network DEA, where the output of the first process (intermediates) becomes the input of the second process. Among many of the two-stage network DEA models, Kao and Hwang (2008) has developed a model where the total efficiency of a DMU is the multiplication of the efficiency scores of two stages, and the weight the intermediate gets is the same whether it is used as the output of the first stage or it is the input of the second stage.

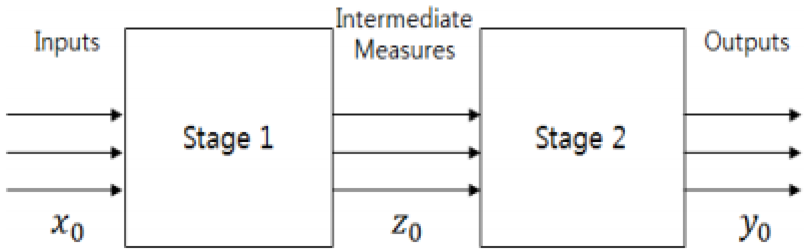


Figure 3 General two-stage process

The CRS input oriented two-stage network DEA suggested by Kao and Hwang calculates DMU 0's efficiency score by the linear equation below.

$$
\begin{aligned}
\max \quad & u y_0 \\
s.t. \quad & wZ - vX \leq 0, \\
& uY - wZ \leq 0, \\
& v x_0 = 1, \\
& v,\ u,\ w \geq 0.
\end{aligned}
$$

Here, $X = (x_{ij}) \in R^{m \times n}$, $Z = (z_{dj}) \in R^{D \times n}$, $Y = (y_{rj}) \in R^{s \times n}$, is the data matrix of input, intermediate, and output. Then, v, w, u denote the decision making variables that represent the optimal weight of each elements. For the intermediate, whether it is the output of the first stage or the input of the second stage, the same weight (w) is given. The total efficiency score of the DMU 0 would be $\theta^* = u^* y_0$. The efficiency score for the first stage and the second stage would be respectively $\theta_1^* = w^* z_0$ and $\theta_2^* = u^* y_0 / w^* z_0$. * denotes the optimal solution. Here, the total efficiency is the multiplication of the each processes' efficiency score.

3. Research model and Hypotheses

3.1 Research model

In this paper, 32 Asia-Pacific international airports' efficiency scores are calculated through network DEA model set in the study, and then to answer research questions, these efficiency scores are statistically regressed upon three variables. Data collection and model composition was done on Excel, and then Network DEA was performed on EnPas developed by Manhee Park. Non-parametric statistics and regression testing was done through R and IBM SPSS.

The network DEA model used in this study to analyze Asia-Pacific region's airport efficiency is as below, which applied Kao and Hwang's two stage network model. This study views the airport process to be composed of two processes; physical management stage that are related to passenger and cargo transportation and monetization stage where the throughput generated at the first stage created financial value. In the perspective of general corporate management, the first stage is the production stage, and the second stage can be seen as the sales stage. The input, intermediate, and output variables were selected in consideration of factors used in previous studies, factors that are generally regarded as to be related to airport operation, and data availability. The operational definition is also presented in table 2.

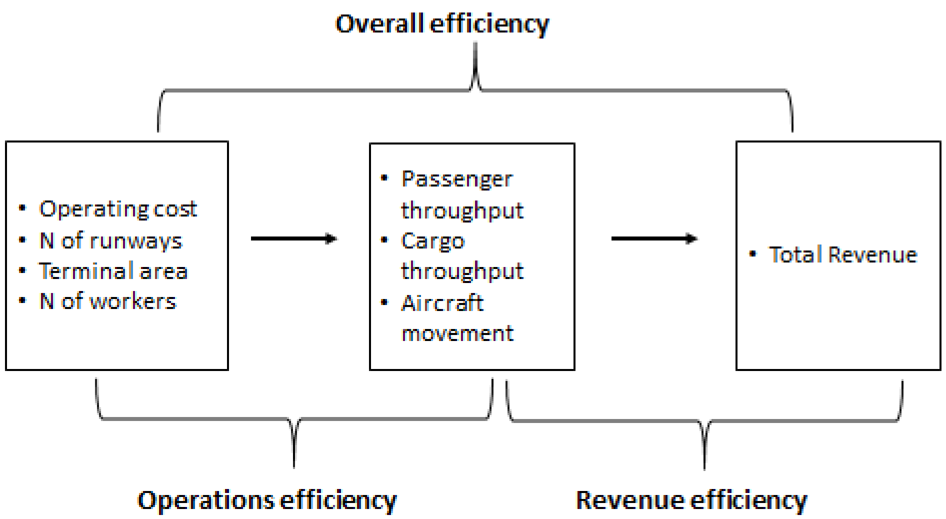


Figure 4 Input, output, and intermediate factors in the two-stage airport process

Table 2 Definition of input, output, and intermediate factors

Variable		Unit	Definition
Inputs	Operating cost	Million dollars	Total annual operating costs including labor and facility costs
	Number of runways	-	Total number of runways in the airport
	Terminal area	Meter sq	Total terminal area size in the airport
	Number of workers	-	Total number of workers employed in the airport
Intermediates	Passenger throughput	Thousand	Total number of domestic and international passengers shipped
	Cargo throughput	Ton	Total number of domestic and international cargo shipped
	Aircraft movement	Times	Total number of domestic and international aircraft movement
Outputs	Total revenue	Million dollars	Total annual airport revenue

Liebert and Niemeier (2013) provide an in-depth explanation in table 3 to further elaborate on the selection of input, intermediate and output variables. Inputs are usually composed of capital, labor, materials and other external services that handle traffic volume and non-aeronautical services.

Thus all of these aspects were covered in comprising the input elements. Traditionally, passenger, cargo and aircraft exclusively comprised the output as airports in the past were primarily focused on providing service to passengers, cargo and flights. However, with the deregulation of airport industry, airports are now also seen as commercial enterprises, which brought emphasis in financial outputs as well. Thus, this paper selected passenger, cargo and aircraft throughput as the NDEA's intermediate variables, and total revenue as output.

Table 3 Inputs and Outputs in Airport Benchmarking Studies

Inputs	Outputs
Capital • Physical infrastructure • Monetary measure • Capacity measure	**Desirable outputs** *Aeronautical side* • Number of passengers • Number of air transport movements • Work load units Monetary measure Percentage of on-time operations *Non-aeronautical side* • Non-aeronautical revenues
Labour • Number of employees • Number of full-time equivalent • Staff costs *Materials and outsourcing* • *Operating costs* *Other* • Distance to city centre	**Undesirable by-products** *Delays* • Delayed air transport mocements • Time delays *Noise* • Aircraft noise (surcharge)

3.2 Hypotheses

The aim of this paper is to analyze the efficiency of Asia-Pacific airports in an elaborate manner, and then examine the relationship between several environmental factors and airport efficiency level. To do this, the previous section presented the NDEA model to calculate the efficiency score of each airport. This section presents the hypotheses related to research questions and how they are developed.

First, this paper examines whether the percentage of Low-Cost Carrier influences the level of airport efficiency in Asia-Pacific region. Not much study has been conducted on the relationship between LCC percentage and airport efficiency, but majority of the studies support the positive relationship between the two. Coto Millan et al (2014) stated that adapting to LCCs operational needs such as short turnaround time may induce or force airports to be more efficient, and that along with the traffic increases brought about by LCC which demands to pay lower landing fee, cost reductions will be realized to lower charges. Also, Bottasso et al (2012) asserted that the intensification of traffic volumes brought by LCC may have direct positive effects on airports' revenues from commercial non-aeronautical activities. Lastly, Cavaignac and Petiot (2017) concluded that LCCs' entry to airline markets stimulates airports' productivity improvements, which in turn positively affects total factor productivity and efficiency. Based on the above descriptions, the first hypotheses of the paper are as below:

H1: LCC percentage positively affects airport efficiency.

H1 a: LCC percentage positively affects airport's operations efficiency.

H1 b: LCC percentage positively affects airport's revenue efficiency.

H1 c: LCC percentage positively affects airport's overall efficiency.

Second, this paper tries to examine whether the size of an airport significantly affects the level of its efficiency. The size of the airport is classified according to Martin-Cejas' classification. Units of Traffic transported (UT) is calculated according to the equation below.

$$\mathrm{UT} = \text{Passenger throughput} + \text{Cargo throughput}(kg)/100$$

An airport is seen as a large airport when its $\mathrm{UT} \geq 4 * 10^7$, and is seen as small otherwise. Larger airports are expected to have higher efficiency than smaller ones due to economies of scale (Coto Millan et al, 2004. Humphreys et al, 2002). Also, efficiency difference seems to be attributable to differences in the size of facilities, capital investment, location, and other operational characteristics (A. Assaf, 2009). The size of the airport was found to be important factors in determining the operational performance and efficiency of airports (Pels et al, 2003). Thus, the second hypotheses follow as below:

> H2: Large airports' efficiency is significantly higher than that of small airports.
>
> > H2 a: Large airports' operations efficiency is significantly higher than that of small airports.
> >
> > H2 b: Large airports' revenue efficiency is significantly higher than that of small airports.
> >
> > H2 c: Large airports' overall efficiency is significantly higher than that of small airports.

The last research question this paper poses is the relationship between the airport ownership and the level of airport efficiency. Butler (1985) defined privatization as transfer of functions of organizations from public sector to private sector, whether wholly or partially. With the intention to reduce government involvement, to minimize costs, and to maximize productivity, a wave of airport privatization began in the late 1980s in the UK. The British government included BAA (British Airports Authority) to its SOE privatization program, which marked the start of private sector stepping into to airport industry, an industry that was largely seen as a public sector that is to be managed by the government. Soon after, Germany, France and other European countries followed the airport privatization movement by partially privatizing their airports and some airports in Asia such as Shanghai Pudong, Beijing, and Bangkok airports also sold some of its share to the private sector (Gillen and Niemeier, 2008). Airport privatization can be largely classified into five categories, which are TS, IPO, PF, Operation Concession and Management Contract. These will not be discussed in detail as this paper intends to divide the group to test the hypothesis by whether the private sector participates in the ownership or not, rather than how much the private sector participates in the management.

Thomas Ivanko et al (2013) stated several advantages of airport privatization, such as ease of the budget restrictions, increase of the activeness of airport operation with stronger financial motivation. Also, Parker (1999) stated the main purpose of privatization to be improvements in competition and operating efficiency by introducing new commercially focused management styles and marketing skills. Lastly, Vogel (2006) states that privatized airports operate more cost-efficiently, and receive higher returns on total assets. With the base of literature stating the privatization's aim to capture growth orientation strategies, the last hypotheses are as below:

> H3: Private airports' efficiency is significantly higher than that of public airports.
>
> > H3 a: Private airports' operations efficiency is significantly higher than that of public airports.
> >
> > H3 b: Private airports' revenue efficiency is significantly higher than that of public airports.
> >
> > H3 c: Private airports' overall efficiency is significantly higher than that of public airports

4. Measurement

4.1 Data collection

Data for the paper's network DEA model and regression were largely collected from 2019 ATRS Airport Benchmarking Report, published by ACI (Airport Council International). This report presents world's airport data of 2017. ATRS Airport Benchmarking Report is published annually, and through this report, data such as passenger throughput, cargo throughput, aircraft movement, number of runways, number of workers, and terminal area were extracted. Financial data and additional information were collected from each airport's annual report or website.

4.2 DEA settings

To perform DEA analysis, one has to select whether to use an input-oriented model or an output-oriented model. This paper adopted input-oriented model, which is a model that compares the amount of input each DMU has to invest in order to gain the same amount of output. This is because input variables are relatively easier to control than output variables.

Also, many studies not only in the field of airport industry but also in other industries have reported that input quantity selection emerges as a major decision making issue for many organizations. Thus, this paper uses input-oriented model to measure inefficiencies in input variables of airports.

4.3 Number of DMU (Decision Making Units)

The discrimination power of DEA model can be affected by the number of its DMU, and the number of its input and output variables. When the number of DMUs is relatively much lower than that of input and output variables, the model may become too generous, analyzing many of its DMUs as efficient. There isn't a definite standard as to the number of DMUs that a DEA model should have, but there are generally three standards to this question. Firstly, Banker et al (1984) stated that the number of DMUs should be at least bigger than three times the sum of the number of input and output variables. Secondly, Fitzsimmons (1994) stated that the number of DMUs should be at least bigger than two times the sum of the number of input and output variables. Lastly, Boussofinance et al (1991) stated that the number of DMUs should be at least bigger than two times the multiplication of the number of input and output variables. When each guideline is applied to the paper's model, the suggested minimum number of DMUs is respectively 24, 16, and 24. This paper examines 32 Asia-Pacific international airports, which is above all the suggested minimum number of DMUs. Thus, this paper's number of DMU is seen to have adequate discrimination power.

5. Analysis and Results

5.1 Descriptive statistics

Table 4 presents the sample airports used in this study and their characteristics. There are total 32 airports, all located in Asia-Pacific region. Military purpose airports were excluded from the sample as they were considered unfit for the purpose of the paper. Also, group airports were not taken into the sample due to the unavailability of the separate data of each airport in the group. Based on the collected data, descriptive statistics for input, intermediate, and intermediate factors is as presented in the Table 5.

Table 4 Sample airports and their characteristics

N	Airports	IATA code	Country	Ownership	Size
1	Adelaide	ADL	Austrailia	private	Small
2	Aukland	AKL	New Zealand	public	Small
3	Brisbane	BNE	Austrailia	private	Small
4	Chhatrapati	BOM	India	private	Large
5	Bai Yun	CAN	China	public	Large
6	CEBU	CEB	Philiphines	public	Small
7	Jakarta Soekarno-Hatta	CGK	Indonesia	private	Large

8	Christchurch	CHC	New Zealand	public	Small
9	Jeju	CJU	ROK	public	Small
10	Sri Lanka	CMB	Sri Lanka	public	Small
11	Cairns	CNS	Austrailia	public	Small
12	Indira Gandhi	DEL	India	public	Large
13	Darwin	DRW	Austrailia	private	Small
14	Seoul Gimpo	GMP	ROK	public	Small
15	Antonio B. Won Pat	GUM	Guam	public	Small
16	Meilan	HAK	China	public	Small
17	Hongkong	HKG	Hongkong	public	Large
18	Haneda	HND	Japan	private	Large
19	Incheon	ICN	ROK	public	Large
20	Kansai	KIX	Japan	private	Small
21	Kuala Lumpur	KUL	Malaysia	public	Large
22	Tokyo Narita	NRT	Japan	public	Large
23	Gold Coast	OOL	Austrailia	public	Small
24	Beijing Capital	PEK	China	private	Large
25	Penang	PEN	Malaysia	public	Small
26	Perth	PER	Austrailia	private	Small
27	Gimhae	PUS	ROK	public	Small
28	Shanghai Pudong	PVG	China	private	Large
29	Singapore Changhi	SIN	Singapore	public	Large
30	Sydney	SYD	Austrailia	private	Large
31	Shenzhen Bao'an	SZX	China	public	Large
32	Taiwan Waoyuan	TPE	Taiwan	public	Large

Table 5 Descriptive statistics for input, output, and intermediate factors

Factors	Average	Standard Deviation	Max	Min
Inputs				
Operating cost (million US$)	340	359	1286	11.82
Number of runways	2.25	0.76	4	1
Terminal area (m^2)	471239	438243	1382000	27000
Number of employees	1336	1726	6416	68
Intermediates				
Passengers Throughput	36177	27134	95786	2246
Cargo Throughput	953	1200	4600	0.43
Aircraft movement	241	161	597	27
Outputs				
Revenue (million US$)	585	649	2374	3.98

In addition, as a preliminary data for the efficiency evaluation, correlation of the input, intermediate, and output variables were tested through Pearson correlation analysis. When forming a DEA model, the selection of variables must be isotonic, i.e., the value of output variables cannot decrease when input variables are increased (Lin and Hong, 2006).

The Pearson correlation analysis result shown in table 6 implies that all the input and output have a strong correlation to one another. Thus, this implies that this model can be used as a tool of efficiency measurement (U. Kim, 2009)

Table 6 Pearson Correlations Analysis of input, output, and intermediate factors

		operating_cost__million_US__	Runways_n	terminal_area__m2_	workers_n	passengers_T_000_	Cargo_T_000_	aircraft_movement_000_	revenue_million__
operating_cost__million_US__	Pearson 상관	1	.433*	.599**	.521**	.612**	.688**	.624**	.577**
	유의확률 (양측)		.013	.000	.002	.000	.000	.000	.001
	N	32	32	32	32	32	32	32	32
Runways_n	Pearson 상관	.433*	1	.426*	.238	.670**	.454**	.686**	.048
	유의확률 (양측)	.013		.015	.190	.000	.009	.000	.792
	N	32	32	32	32	32	32	32	32
terminal_area__m2_	Pearson 상관	.599**	.426*	1	.467**	.728**	.639**	.719**	.540**
	유의확률 (양측)	.000	.015		.007	.000	.000	.000	.001
	N	32	32	32	32	32	32	32	32
workers_n	Pearson 상관	.521**	.238	.467**	1	.433*	.493**	.504**	.377*
	유의확률 (양측)	.002	.190	.007		.013	.004	.003	.033
	N	32	32	32	32	32	32	32	32
passengers_T_000_	Pearson 상관	.612**	.670**	.728**	.433*	1	.735**	.980**	.472**
	유의확률 (양측)	.000	.000	.000	.013		.000	.000	.006
	N	32	32	32	32	32	32	32	32
Cargo_T_000_	Pearson 상관	.688**	.454**	.639**	.493**	.735**	1	.702**	.543**
	유의확률 (양측)	.000	.009	.000	.004	.000		.000	.001
	N	32	32	32	32	32	32	32	32
aircraft_movement_000_	Pearson 상관	.624**	.686**	.719**	.504**	.980**	.702**	1	.467**
	유의확률 (양측)	.000	.000	.000	.003	.000	.000		.007
	N	32	32	32	32	32	32	32	32
revenue_million__	Pearson 상관	.577**	.048	.540**	.377*	.472**	.543**	.467**	1
	유의확률 (양측)	.001	.792	.001	.033	.006	.001	.007	
	N	32	32	32	32	32	32	32	32

*. 상관관계가 0.05 수준에서 유의합니다(양측).

**. 상관관계가 0.01 수준에서 유의합니다(양측).

5.2 DEA results

The results of 32 airports' overall efficiency, operations efficiency and revenue efficiency are presented in table 7. The distribution of each efficiency score and the means are as stated in figure 5, 6, 7and table 8.

Table 7 Overall, operations, and revenue efficiency scores of airports

IATA Code	Scores		
	Operations Efficiency	Revenue Efficiency	Overall Efficiency
ADL	0.9039	0.1896	0.171379
AKL	0.8596	0.2511	0.215846
BNE	0.9779	0.2959	0.289361
BOM	1	0.0903	0.0903
CAN	0.7316	1	0.7316
CEB	1	1	1
CGK	1	0.0855	0.0855
CHC	0.6917	0.318	0.219961
CJU	1	0.0643	0.0643
CMB	0.6365	0.1317	0.083827
CNS	0.5377	1	0.5377
DEL	1	0.0241	0.0241
DRW	0.5803	1	0.5803
GMP	0.7709	0.074	0.057047
GUM	0.4825	0.0944	0.045548
HAK	1	0.0804	0.0804
HKG	1	0.3203	0.3203
HND	1	0.0339	0.0339
ICN	0.7971	0.3273	0.26089083
KIX	0.8577	0.055	0.0471735
KUL	1	0.064	0.064
NRT	0.9217	0.045	0.0414765
OOL	0.6437	0.3083	0.19845271
PEK	1	0.0134	0.0134
PEN	0.3471	1	0.3471
PER	1	0.0024	0.0024
PUS	0.7076	0.0994	0.07033544
PVG	0.962	0.0134	0.0128908
SIN	0.6838	0.0279	0.01907802
SYD	0.9175	0.0287	0.02633225
SZX	0.8458	0.2072	0.17524976
TPE	1	0.1501	0.1501

Table 8 Efficiency score averages

Operations efficiency	Revenue efficiency	Overall efficiency
0.839269	0.262363	0.189383

Figure 5 Operations efficiency score distribution

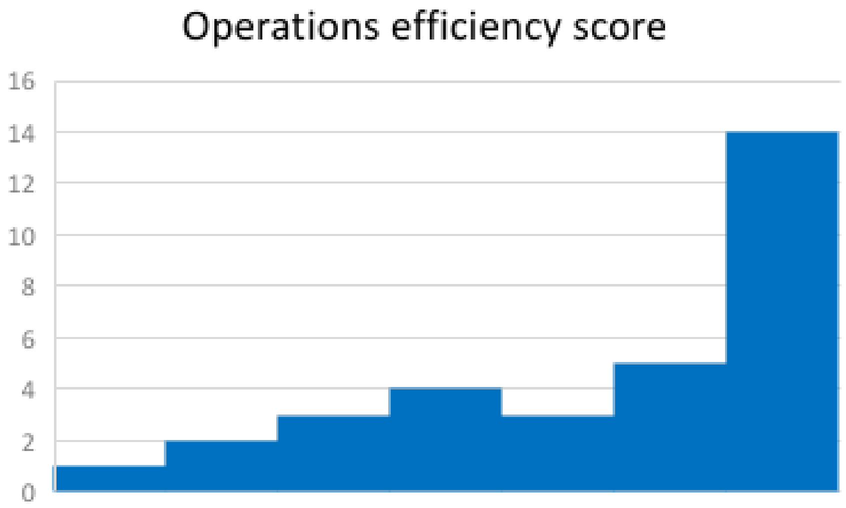


Figure 6 Revenue efficiency score distribution

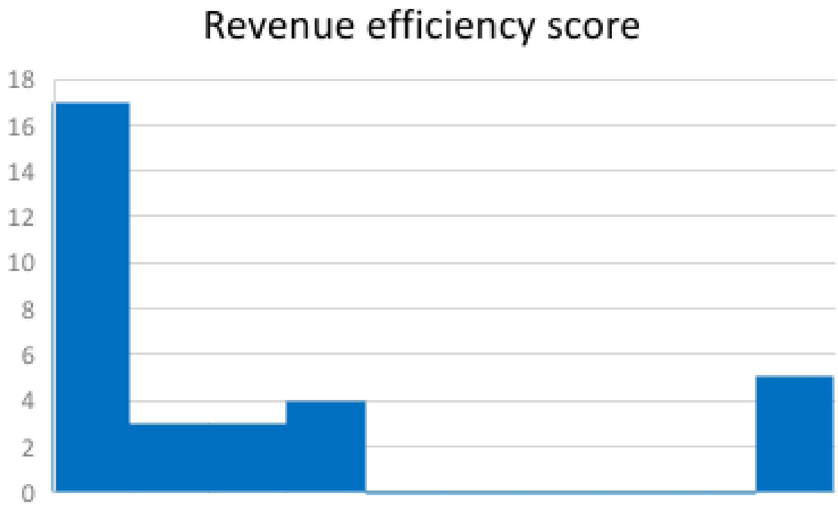
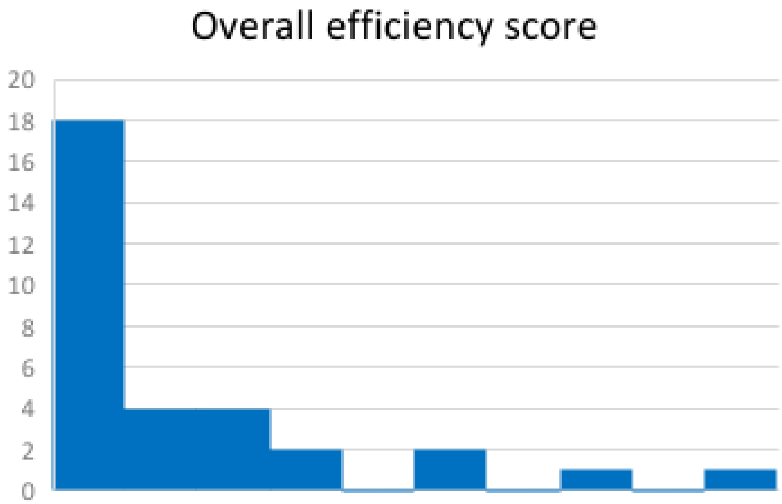


Figure 7 Overall efficiency score distribution



Looking at the network DEA results, the overall efficiency is generally very low, with its mean 0.189383. Cebu airport was the only airport that was evaluated to be efficient in overall perspective. While the mean of operational efficiency was 0.839269 with 11 airports ((BOM, CEB, CGK, CJU, DEL, HAK, HKG, HND, KUL, PEK, PER) as efficient, the revenue efficiency's average was only 0.262363, with 5 airports (CAN, CEB, CNS, DRW, PEN) efficient. It can be seen that the reason why the Asia-Pacific airports have low overall efficiency comes from the revenue process rather than the operational process.

5.3 Regression analysis result

In this study, to examine the statistical relationship between the efficiency score and the variables related to the research question, Wilcoxon rank-sum and Kolmogorov-Smirnov Test were performed for the discrete variables, and regression analysis was performed for the continuous variables. Theoretically, we assume that we do not know the distribution of the DEA's efficiency score, so the normality was not tested.

To examine whether the LCC share affects the airport efficiency, regression between the two variables was performed. The scatterplot of efficiency scores against the LCC % is as below figure 8, 9, and 10.

The regression analysis results are as presented in table 9, 10, and 11. No significant statistical relationship was found between the LCC % and any of the three efficiency scores. Thus, H1 was completely rejected.

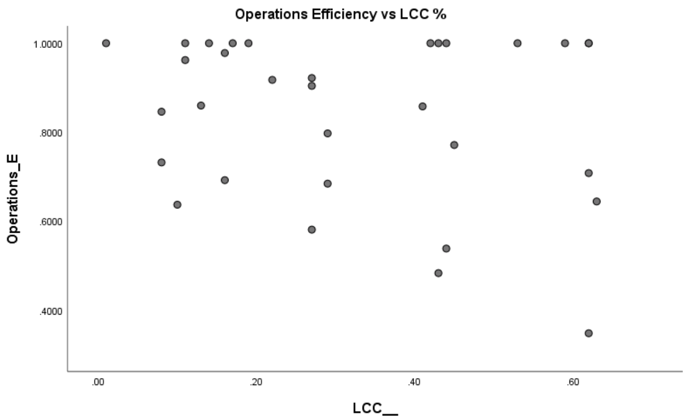


Figure 8 LCC % vs. operations efficiency

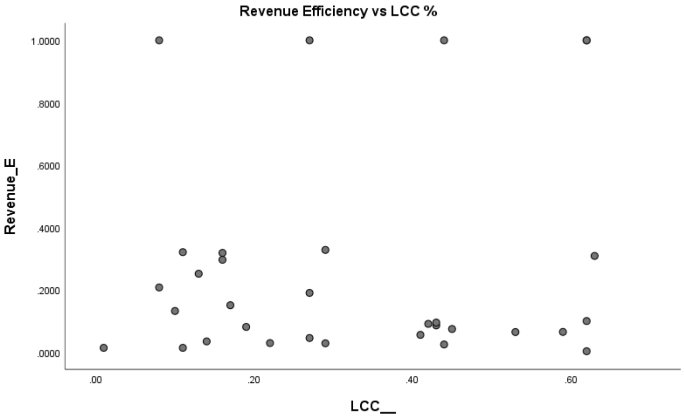


Figure 9 LCC % vs. revenue efficiency

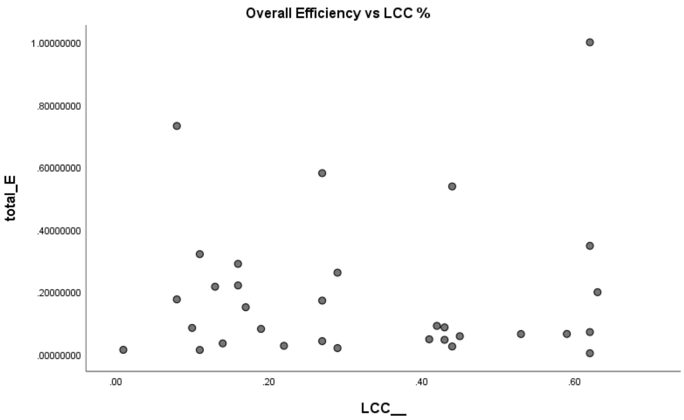


Figure 10 LCC % vs. overall efficiency

Table 9 Linear regression on %LCC vs. operations efficiency

Coefficients:				
	Estimate	Std Err.	t value	Pr(>|t|)
(Intercept)	0.898	0.063	14.213	0
% LCC	-0.183	0.168	-1.085	0.287
Adjusted R-squared: -.194, p-value=0.287				

Table 10 Linear regression on %LCC vs. revenue efficiency

Coefficients:				
	Estimate	Std Err.	t value	Pr(>|t|)
(Intercept)	0.193	0.117	1.649	0.109
% LCC	0.214	0.313	0.685	0.499
Adjusted R-squared: .214, p-value=0.499				

Table 11 Linear regression on %LCC vs. overall efficiency

Coefficients:				
	Estimate	Std Err.	t value	Pr(>|t|)
(Intercept)	0.166	0.081	2.052	0.049
% LCC	0.073	0.215	0.34	0.736
Adjusted R-squared: .062, p-value=0.736				

The paper then examined the relationship between the airport size and the efficiency scores. The efficiency score distribution according to size is presented in figure 11, 12, and 13.

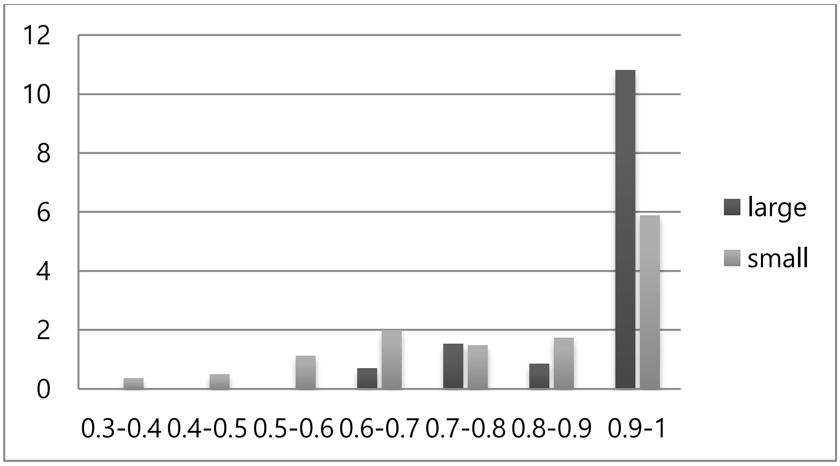


Figure 11 Operations efficiency scores by size

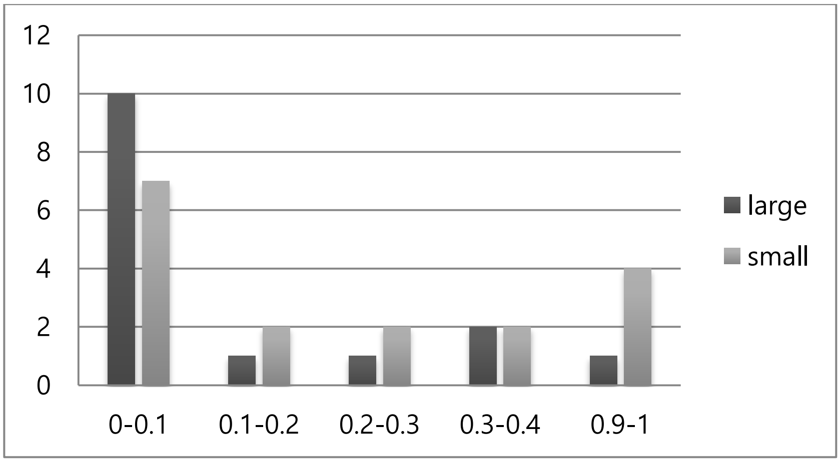


Figure 12 Revenue efficiency scores by size

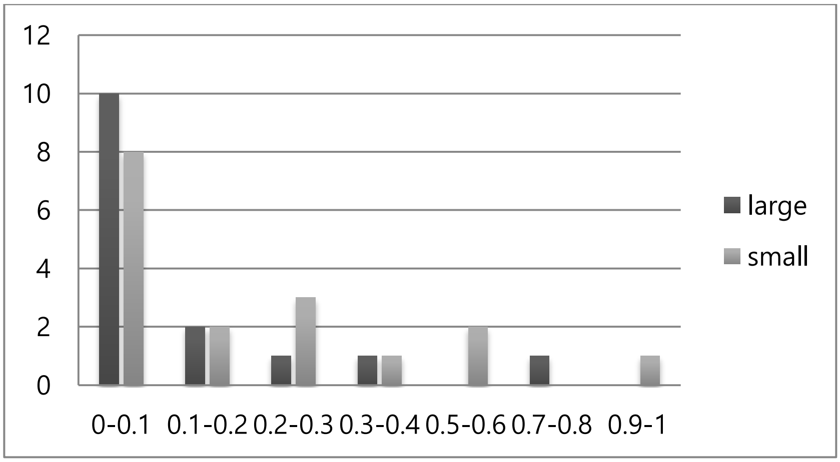


Figure 13 Overall efficiency scores by size

Table 12 Efficiency score averages by size

Airport Size	Operations efficiency	Revenue efficiency	Overall efficiency
Large	0.923967	0.162073	0.136608
Small	0.764535	0.350853	0.235949

Table 13 Wilcoxon rank-sum and Kolmogorov-Smirnov test results on efficiency differences by size

H_0		P-value		
		Operations efficiency	Revenue efficiency	Overall efficiency
Large = Small	MW	0.022**	0.027**	0.034**
	KS	0.019**	0.020**	0.020**

* p<0.1, ** p<0.05, ***<0.01

Comparing the efficiency score average presented in table 12, large airports exceed small airports only in operations efficiency. For revenue efficiency and overall efficiency, small airports had higher means. To test if this difference is statistically significant, Wilcoxon rank-sum test (MW) and Kolmogorov-Smirnov test (KS) were performed to test the null hypothesis assuming no difference between large and small airports. As a result, all three efficiency scores showed statistically significant difference at the 0.05 level. Thus, large airports have higher operations efficiency, while small airports have higher revenue and overall efficiency. Thus, H2 is partially accepted as the paper hypothesized large airports to have higher efficiency in all aspects.

Lastly, airports were divided into two groups according to their ownership form: public and private. The efficiency distribution of the two groups looks like figure 14, 15, and 16.

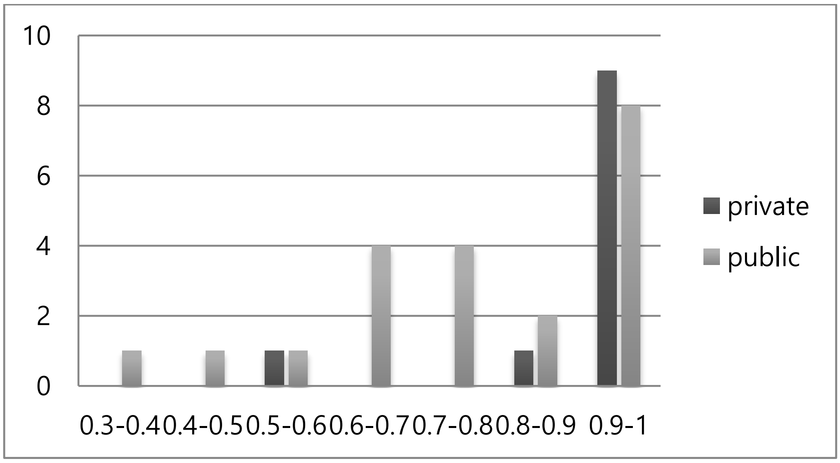


Figure 14 Operations efficiency scores by ownership

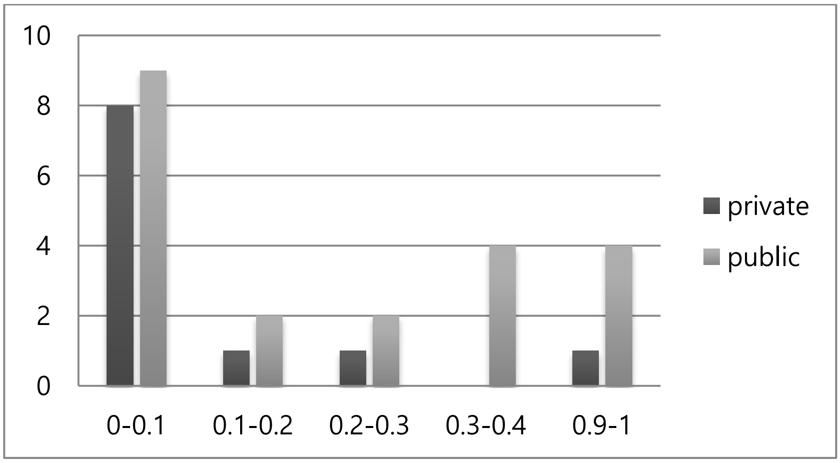


Figure 15 Revenue efficiency scores by ownership

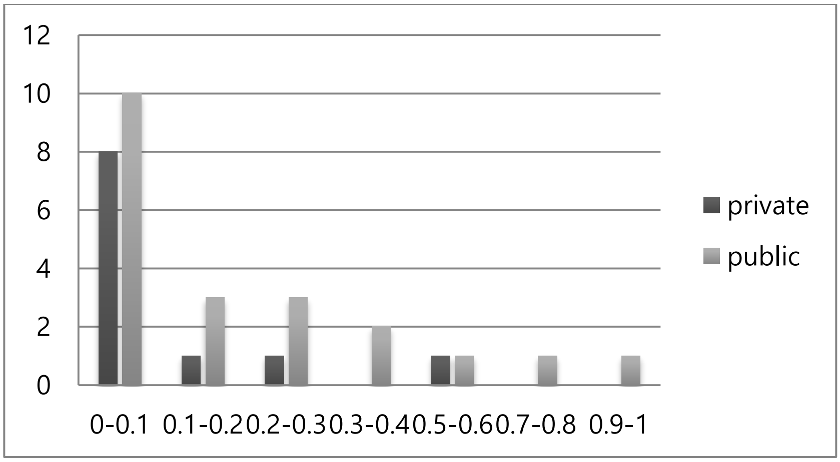


Figure 16 Overall efficiency scores by ownership

Comparing the efficiency score average presented in table 14, private airports exceed public airports in revenue efficiency and overall efficiency. For operations efficiency, public airports had higher means. To test if this difference is statistically significant, again Wilcoxon rank-sum test (MW) and Kolmogorov-Smirnov test (KS) were performed. As a result, revenue and overall efficiency scores showed statistically significant difference at the 0.05 level. Thus, private airports have higher revenue efficiency and overall efficiency than public airports. Difference in operations efficiency was not statistically significant. Thus, with H3b and H3c supported, H3 was partially supported.

Table 14 Efficiency score averages by size

Airport Size	Operations efficiency	Revenue efficiency	Overall efficiency
Public	0.914183	0.156842	0.117499
Private	0.79432	0.325675	0.232513

Table 15 Wilcoxon rank-sum and Kolmogorov-Smirnov test results on efficiency differences by ownership

H_0		P-value		
		Operations efficiency	Revenue efficiency	Overall efficiency
Public = Private	MW	0.169	0.041**	0.041**
	KS	0.095	0.034**	0.034**

* p<0.1, ** p<0.05, ***<0.01

6. Discussion

6.1 Conclusion

This paper considered airport process as a two stage process with a physical operation stage related to transporting passengers and cargo, and a revenue stage where the operation is creating financial value. With network DEA model, the efficiency score of 32 Asia-Pacific international airports was analyzed. With empirical analysis, internal and external factors such as the share of Low-Cost Carrier, airport size and airport ownership were examined as to what influence they make upon the efficiency level of the airport.

Looking at the network DEA results, the overall efficiency of the sample airports were generally very low, and the low level of revenue efficiency appears to be the cause. This is consistent with previous literature, which states that improvement in commercial, or revenue efficiency seems to be more crucial than that of production/operation efficiency (Yu., 2010, Kang., 2015, Liu., 2016, Yoo et al., 2017). This implies that airport industry, as an infrastructure business, tends to focus more on passenger service or operational performance than on revenue. International aviation organizations such as ACI also announce airport rankings based on the number of passengers or shipping record. This may be due to the long history of aviation industry being a pubic organization. However, to improve the overall efficiency level of Asia-Pacific airports, efforts to higher the revenue efficiency is necessary as well.

There was no statistically significant relationship found between the percentage of LCC and airport efficiency in Asia-Pacific region. This may be due to lack of process transformation to fully adapt to LCCs. In other continents, LCCs are first launched in secondary airports to evade from the competition with FSCs. Southwest airlines started its business from a small secondary airport at Dallas Love Field in 1960s. Traditionally many LCCs use secondary airports because of the availability of slots, spare capacity and low aeronautical cost (Choo and Oum, 2013). Yet, Asia has much less secondary airports in metro areas that are available for LCCs (Zhang et al, 2008). Primary airports also need to differentiate their services that often involve more than changes in operational processes but design of airport terminals. (Hanaoka and Saraswati, 2011), and Asia-Pacific region may not have had sufficient transformation period to make a synergy with LCC.

H2 was partially supported, showing large airports to have higher operations efficiency. This seems to be due to economies of scale in terms of their physical resources (S. Yoo et al, 2017., Coto Millan et al, 2014., Humphreys et al, 2002.,Barros and Dieke, 2008.). However, in revenue and overall efficiency, small airports had higher scores. In the airport industry, it is likely that supply is characterized by increasing long-run cost at quite moderate levels of output (Monopolies and Mergers Commission, 1991). Also, large airport regulation under the assumption that airports with size are natural monopolies may lead to inefficiency (Starkie, 2001). For these possible explanations, large airports came out to have higher operations efficiency, but lower revenue and overall efficiency.

H3 was also partially accepted, with private airports having significantly higher revenue and overall efficiency scores than the public airports. No significance was found in the difference of two groups in terms of operations efficiency, showing not much difference in terms of airports' fundamental task performance. Given that the landing charge and the airport charges of private airports are higher than that of public airports, it can be concluded that private airports are much more profit driven than its counterpart, showing higher revenue per passenger and revenue per flight as presented in table 16. This is also consistent with many previous studies, which state that privatized airports intend to maximize their revenues, whereas public airports aim to optimize traffic (Vasigh and Haririan, 2003).

Table 16 Revenue per passenger/flight (2015 ATRS Airport Benchmarking Report)

Category	Revenue per passenger ($)	Revenue per flight ($)
Public	15.84	1,844
Private	25.33	3,298

6.2 Implications

This study has decomposed the efficiency of airports into two processes, operations and revenue making process, and examined their determining factors. Like the literature, this study has performed DEA and regression analysis, and this study contributes to the literature in that while many previous studies has set the final efficiency as the sole dependent variable, this study aimed to figure out determinants for each decomposed efficiency processes as well. Also, few studies has examined how LCCs affect airport's performance or operating strategies, despite the fact that the market share of LCCs are continuously increasing. Given that with ongoing deregulation trend in aviation industry, LCC will have more and more room for growth.

Asia-Pacific airports are managed at a low efficiency level, and to improve this efficiency, there needs to be managerial efforts to turn the level of passengers and cargo throughput to higher profit. Also, given that LCCs has been introduced to Asia-Pacific region quite recently compared to other regions, groundwork to create synergy effect between airports and LCCs are needed. Adapting to LCC-appropriate business model will take time and cost, and possibly some policies or regulation changes. Large airports are operationally efficient, but lag behind in revenue and overall efficiency. Solutions need to be brought up to lead high level of operational efficiency to better profit. Also, given that the participation of private sector in the airport industry plays a positive role in airport efficiency, various strategies could be taken into account. While bearing in mind that privatization cannot be seen as a universal solution and should not be separated from the economics of competition and regulation, (Vickers and Yarrow, 1991), decisions could be made to appropriately harmonize publicness and efficiency.

7. Limitations and Future Research

The data of this study was confined to one year data, the 2017 period. Although it is the most recent data open to the public, the usage of a time series data and Malmquist analysis would have made a more dynamic examination possible. Also, this study was not able to determine why LCC did not have a significant impact on airport efficiency in Asia-Pacific region, which is quite different to other study results performed in other continents. By including regions that LCC does play a significant role in airport efficiency, a more in-depth comparison would be possible. Lastly in terms of limitation regarding data, this study was not able to include airports affiliated to airport groups. For example, airports in India, as they are synthetically managed by Airports Authority of India, could not be included to the sample due to data unavailability. As India has relatively well established LCC system, this comes as a limitation to the study.

Secondly, as for the variables, it would be meaningful to include qualitative performance indicators, both into the DEA model and regression analysis. This study only considered quantitative factors, but as the airport industry is getting more and more servitized, factors such as service quality and customer satisfaction would also bring meaningful implications. Also, while this paper classified the ownership form of airports largely into public and private airports, as there are various types and extent to which public sectors can participate in the management, a more elaborate classification could be possible.

Some of the hypotheses may have been somewhat implying the results, in that the standard of the airport size was based on the throughput and the main purpose of privatization is to capture growth orientation strategies inherent to private management. Thus, it may be self-obvious that these have higher efficiency than its counterparts. However, the literature had indefinite conclusion as to these research questions, and through decomposing the efficiency process, the study was able to find out in which process they have relative strength and in which process they don't. Therefore, the future study may control the condition more precisely, by controlling airport size with the floor space (m^2) for instance.

Lastly, DEA models have internal limitations, where the efficiency score is not an absolute efficiency level but only a relative measure. This means that DMUs' efficiency level may change according to different DMU groups, variables, or time frame. This is why much contemplation should be made in forming a DEA model, considering much literature. Future research could also consider forming one integrated regression model and determine relative significance of each independent variable.

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국 문 초 록

2단계 네트워크 DEA를 이용한 아태 지역 주요 공항 성과 분석

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본 논문은 항공 산업이 물류 운송 수단이자 여행 수단으로 대두되고 있음에 주목하여, 승객과 항공을 매개하는 역할의 공항의 효율성 (Efficiency) 측정에 대한 연구를 진행하였다. 향후 가장 큰 성장을 보일 것으로 예상되는 아시아 태평양 지역의 공항 효율성을 성과 측정의 도구이자 비모수적 (Non-parametric) 연구 방법인 DEA로 분석하였다. 특히, 2단계 네트워크 DEA 방법론을 활용하여 공항 프로세스의 효율성을 운영 효율성과 수익 효율성으로 세부화하여 분석하였다. 공항의 운영비용과 활주로 수, 터미널면적, 종업원 수를 투입물로 선정하고, 여객 처리량, 화물처리량, 운항 횟수를 중간 산출물로 두었으며, 공항 총 수익을 산출물로 두어 투입 지향 모형으로 2단계 네트워크 DEA를 실시하였다.

이에 추가적으로 회귀 분석과 비모수 검정법을 실시하여 효율성 점수와 다양한 환경변수들 간의 통계적 방법을 분석하였다. 이를 통하여

공항 크기, 공항 소유 형태, 그리고 저가 항공사 비율이 어떠한 영향을 미치는 지를 탐색하였다.

분석 대상 공항들의 효율성은 대체적으로 매우 낮았고, 비효율적인 수익 프로세스가 낮은 총 효율성의 원인임을 알 수 있었다, 또한, 아직 아태지역 공항 효율성에 저가 항공사가 기여하는 바가 낮아 저가 항공사 비율과 공항 효율성 사이에 유의미한 관계가 나타나지 않았다. 공항 규모나 소유 형태가 공항 효율성 프로세스 중 어떠한 부분에서 공항 효율성 차이에 기여하는 지를 알아냄으로써 효율성이 낮은 공항들에 대한 시사점과 개선 목표를 제시함과 동시에 향후 공항 경쟁력을 강화하기 위한 참고자료로 활용되기를 목적으로 하였다.

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주요어 : **자료포락분석, 공항 효율성, 아태 지역, 2단계 네트워크 DEA**
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