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THE MEASURE OF AIRPORT EFFICIENCY AND OPERATIONAL CAPABILITIES IN SOUTHERN THAILAND

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Abstract

Eight provinces in Thailand's south tourism-related airports are expected to push for more significant airport expansion. In response to the expansion of the tourism industry in each province of the southern region and the increasing use of services from people in the provinces and neighboring areas, the problem of airports in the eight provinces consists of inefficiency in operating systems and service management. The construction and expansion of infrastructure projects that do not meet the needs of service users need to be improved. Therefore, this study chose a performance measurement tool to help analyze the data using slack-based measure data envelopment analysis (SBM-DEA) to measure the efficiency and operations of all eight airports quantitatively. In addition, the research team used qualitative data to help determine the problem of the input and output factors of all eight airports and used the Tobit regression model to analyze factors affecting the operational efficiency of all eight airports in the southern region of Thailand. According to the study, Nakhon Si Thammarat Airport (NST), Phuket Airport (HKT), Krabi Airport (KBV), Surat Thani Airport (URT), Hat Yai Airport (HDY) and Chumphon Airport (CMJ) also lacked operational efficiency. Almost all airports should have improved input factors, such as number of check-in counters, terminal area, parking area lots and pit stops. Output factors such as number of flights and number of goods. It was also found that Chumphon Airport (CMJ) and Hat Yai Airport (HDY) were also the least efficient in operation. Furthermore, factors affecting the operating efficiency of all eight airports in the southern region of Thailand can be sorted from most influencing factors to least as follows: Airport condition (X4), security (X3), and airport staff (X1), respectively.

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Keywords: Airports, Operations, SBM-DEA Model, Efficiency Measurement, Tobit Regression.

Introduction

From 1995 to 2017, the number of air passengers and freight continued to expand (Department of Airports, 2017). It was discovered that eight provinces related to tourism in the southern region have plans to push for the expansion of larger airports. The effort of larger airports was to support the expansion of the southern region's tourism industry in each province and the increasing use of services by people in the provinces and nearby areas. Provincial airports associated with southern Thailand's tourism industry include Ranong, Phuket, Krabi, Trang, Chumphon, Surat Thani, Nakhon Si Thammarat, and Songkhla, which are considered essential airports in southern Thailand. These airports cover both the western and eastern parts of the Peninsula. The primary function of these airports is to support domestic and international passengers, and air freight. Most specially to support inbound and outbound passengers; most passengers are tourists from within the country or abroad. Therefore, airports in these provinces can also generate income for the airport in each province. In addition, this by-product stimulates the flow of money in the province's economy.

Thus, there is a need to accelerate the expansion of the service infrastructure and improve operations as soon as possible. Hence, from the importance mentioned above, it is necessary to accelerate the study of airport efficiency measurement and operational capabilities in the southern region. This will lead to the correct determination of problems in the operation of the airport, knowing how to use the input and output factors, and measuring the operational efficiency and productivity of the limited resources in all eight airports. Simultaneously, it is possible to set directions and policies to improve airport operations in these areas. The problems that arose at the eight airports in the provinces were lack of operational efficiency in system and service management, delayed construction and expansion of the foundation project, and the need to meet the needs of service users. Lack of improvements on the spot, thus affecting the efficiency of all operations within the airport, such as passenger and air freight transportation services, causes inconvenience to those who come to use the service at the airport, causing delays. Parking space is insufficient for passengers who use the service. There must be more than the runway size to accommodate a large aircraft. Therefore, this study uses economic tools to analyze data using the slack-based measure Data Envelopment Analysis (SBM-DEA) encirclement analysis method. The efficiency and operation of all eight airports were measured quantitatively. The main goal of this study is to determine the resource allocation of input and output factors limited within the airports of each province to achieve a balance in operations. Also help determine the direction to improve each (Decision-Making Unit: DMU) using the best decision-making unit as a baseline for inefficient DMUs.

Literature Review

SBM-DEA Approach

The theory of efficiency was invented by Koopmans (1951), who defined the theory of production efficiency, which states that a manufacturer will be productive when he/she cannot produce more than it produces. Later, Debreu (1951) developed a theory of productivity in the form of (Distance Function). The idea is to use the method of measuring the radiation line of products coming out of the production boundary line (frontier). Later, in 1975, M.J. Farrell (1957) proposed the concept of measuring economic performance, characterized as a quantitative tool to compare relative efficiency underestimation to the frontier equation or frontier estimate, and then look at how far away the point being considered is from the border by measuring productivity. The efficiency measurement method can be divided into two categories:1. Data Envelopment Analysis (DEA) is a mathematical method that uses linear programming or nonparametric methods, and 2. Stochastic Frontiers (SFA) are computational methods that use econometrics. Parametric estimation under maximum likelihood (ML) and ordinary least squares (OLS) methods.

The Data envelopment analysis (DEA) method was developed by Charnes et al. (1978). DEA was created as a nonparametric method to measure performance by comparing decision unit sets or Decision-Making Units (DMUs). Most DEA framing analysis methods focus on the optimal activities and performance measures. In 1984, Banker, Charnes, and Cooper took the initiative to expand Charnes' original work by categorizing the return on change in magnitude using the framing analysis method. Subsequently, the BBC model was used (Banker et al., 1984). Subsequently, Tone (2001) developed the SBM framing analysis method using the weighted approach of input fraction, excess, and deficit outputs with scarcity analysis.

According to a review, the SBM-DEA approach was used to correct internal stretches. The DEA data framework analysis methodology using the SBM model can directly match the scarcity of the input and output factors. Performance is measured by considering performance scores between 0 and 1 and determining whether or not there is a relevant decision-making unit on the borderline of a production set; the scarcity of inputs and output factors is zero.

Chang, Y. T. et al. (2014) studied the economic performance measurements and environment of 27 international airlines using the SBM data framework analysis method. He found that Asian airlines performed the best, followed by European and American airlines. High oil consumption rates directly affect the inefficiency of international airlines in economic and environmental contexts.

Tsui, W. H. K., et al. (2014). New Zealand's airport industry has grown significantly in the recent years. However, only a few studies have analyzed the operational efficiency of New Zealand airports. This study aims to explore changes in the efficiency and effectiveness of New Zealand's major airports from 2010 to 2012, using the SBM model and the Malmquist productivity index (MPI), and found that most New Zealand airports increased efficiency and productivity during the period under review. However, the operational sizes should be reduced to operate at the most productive size. The MPI shows that most New Zealand airports have increased efficiency, but declined in terms of technology. Lozano and Gutiérrez (2011) measure the efficiency of 39 Spanish airports between 2006 and 2007. They found that the general output factors considered were the movement of aircraft traffic passengers, movement and product management, unfavourable export factors, such as flight delays, and the average conditional delay of flight delays. The inputs consider the amount of physical infrastructure of the airport and are considered non-discriminatory. Using Data Envelopment Analysis (DEA), the effect on the size of the change and vulnerability of the factor can be analysed.

Desirable and unwanted exports in the SBM Model were found to be more discriminatory. General directional distance function. Additionally, the adverse effects of airport operations lead to more accurate results. The results show that two years have passed since then. More than half of the airports are technically efficient. Choi et al. (2020) analysed the viable sustainability of major airports in China in terms of airport operational efficiency (AOE). This study uses the SBM Model to analyse the inputs and exports of airports and finds that 37 major airports in China had deficient AOE levels, with an average of only 48.2% during the 2016–2019 study period. However, this still lags in terms of global standards.

Most airports in China are self-sufficient. There are two ways for these airports to improve operational efficiency: additional investments in infrastructure, such as airport facilities, and developing a body of knowledge in management. Except for eight airports with efficiency and fixed return, such as Beijing and Guangzhou, etc., Lee H. et al. (2021) conducted a study of the operational performance of 14 Korean airports using data encapsulation analysis under the SBM model. The average efficiency score of all 14 airports for 2014–2018 was an efficiency factor of 0.323, indicating a potential improvement of 0.677, with an international airport efficiency rating of 0.515, higher than that of the domestic airport with an efficiency of 0.131. Among the three international airports, Kimpo, Kimhae, and Jeju performed well. Meanwhile, the Muan and Yangyang airports have efficiency values of 0.068 and 0.037, respectively, indicating inefficiency for domestic airports. Only Gwangju showed slightly higher efficiency from 0.373 average, while other domestic airports all show values less than 0.2.

In addition, the DEA enclosing analysis method using the SBM model was used to analyze efficiency in various industries, such as Deng et al. (2016). A study was conducted to measure water use efficiency and analyze factors at the provincial level in China. Water efficiency was measured in 31 provinces using the SBM data frame analysis method. There is high water use efficiency in developed provinces such as Beijing, Shanghai, and Tianjin. Labor is the main factor contributing to inefficient water use. Lee et al. (2014) analyzed the environmental performance of the deep seaport using the SBM framing analysis method owing to the rapid growth of deep-sea ports. This has caused air pollution problems around the ports. Therefore, it is necessary to conduct a study to determine the most effective port environmental management norms. The study found that Singapore Port, Busan Port, Rotterdam, Kaohsiung, and New York Port were more efficient in managing the environment than other ports. The efficiency of freight forwarding in the Pearl River Delta (PRD) region, comprising Hong Kong, Guangzhou, and Shenzhen, is critical for driving economic growth. However, these ports face many challenges, such as the ability to manage ports, environmental problems, and the expansion of complex transport systems owing to air freight. Therefore, this study uses the Dimensioning-Encapsulated Data Model (SBM-DEA) and DEA's undesirable model. To assess the performance of the three major container ports between 2018 and 2019, based on the decision unit values of the port in the past two years, with Yantian Port, the ninth container terminal was the most efficient, followed by the sixth and seventh containers. In addition, the efficiency of the main container terminal in Guangzhou is less satisfactory than that of the Shenzhen and Hong Kong container ports.

Tobit Regression Approach

Dalei & Joshi, (2020) examined the technical performance of 12 Indian oil refineries from 2011 to 2016 using a two-step approach. Part 1 uses Data Envelopment Analysis (DEA) to assess the technical performance of the refinery, and part 2 applies A Tobit Regression model to describe the variation in performance from the underlying variable. Efficiency analysis showed that the IOCL-Barauni, BPCL-Kochi, and IOCL-Panipat refineries were highly efficient between 2011 and 2016, with an average efficiency greater than 95%. Regression of the Tobit model revealed four key factors that explain the differences in distillation efficiency.

Huynh et al. (2020) studied the capabilities of airports in Southeast Asia using a two-step data analysis method. The strengths and weaknesses of each airport in Southeast Asia were assessed using DEA-SBM analysis. The first was a non-parametric method to measure the performance of nine major airports in each country: Changi Airport (Singapore), Suvarnabhumi Airport (Thailand), Kuala Lumpur Airport (Malaysia), Soekarno Hatta Airport (Indonesia), and Ninoy. Aquino Airport (Philippines), Noi Bai Airport, Tan Son Nhat Airport (Vietnam), Guangzhou Baiyun Airport (China), and Hong Kong Airport (Hong Kong). In the second step, the Tobit model was used to assess the influence of several factors on the efficiency of each airport by summarizing and comparing them; they were able to assess the efficiency of each stage of the airport in seven years.

Sergi et al. (2020) used DEA and Tobit analyses. This study measures the technical performance of 32 Italian airports and examines whether these characteristics affect performance and sustainability. The findings indicate that some Italian aviation hubs are technically efficient. Small airports occupied by low-cost airlines have proven inefficient. Another conclusion of this study is that efficiency and environmental impacts are independent of airport size. However, size is important in determining airports’superior performance.

Wang et al. (2020) studied the environmental sound efficiency of 18 ports among five Chinese port groups using 2012-2016 data, using DEA to analyze their efficiency. In addition, Tobit’s regression model was used to analyze the factors influencing the efficiency of the green port, which revealed that the efficiency of China's green port in general was low. There are many problems with the development of green ports. Compared with the current competitive development model for ports. The proposed development model is conducive to improving the efficiency of China's green ports. In addition, they found that economic development, industrial structure, number of ports, passengers, foreign trade, and regional openness can improve the efficiency of green ports. Nitrogen oxide (NOX) and sulfur oxide (SOX) emissions from ports have significantly negative impacts.

Song, M., et al. (2018) Studied provincial water resource performance measurements in China. The Malmquist-Luenberger Yield index was used based on unwanted results from 30 provinces in China from 2006 to 2015. Then, they analyzed the factors affecting the efficiency of water resource use using the Tobit regression model. The efficiency of water resource use differs noticeably between provinces. Water resource efficiency is related to the level of economic development, and technical improvements are key factors in the efficient use of water resources. The level of economic development has a non-linear influence on the efficiency of water resources. Upgrading the industrial structure and expanding the population can significantly improve the efficiency of water resources. while the impact of water supply and education levels per capita was insignificant.

Input and Output Factor Variables

Carlucci et al. (2018) demonstrated that efficient regional airport management has positive effects, both for reducing congestion at large airports and for better utilization of the existing infrastructure. Regional airports often experience economic vulnerability owing to traffic shortages. Data Envelopment Analysis (DEA). This article analyzes the technical performance of 34 Italian airports between 2006–2016 to determine and verify that there are a number of factors affecting the efficiency and economic sustainability of the regional airport. The research reveals that the size of the airport, presence of low-cost airlines, and air freight volume have a great influence on the technical efficiency and size of airports in Italy.

Hong, S.-J., & Jeon, M. (2019) studied low-cost carrier (LCC)-dedicated terminals and focused on the feasibility of regional airports in France based on technical performance using data encapsulation. Key component analysis, the Malmquist productivity index, and regression analysis using bootstrap. To face the current competitive environment, regional airports in France use strategies such as the construction of low-cost airline terminals and construction of low-cost carrier (LCC)-dedicated terminals (LCCTs) at a lower cost to attract more LCC.

Lozano and Gutiérrez (2011) used the SBM model to measure the performance of 39 Spanish airports in 2006 and 2007. Common outcomes include movement of aircraft traffic. Passenger movement and handling of air freight. Adverse outcomes included the percentage of flight and conditional delays. An analysis of the adverse effects of airport operations yields more accurate results. The results show that in the last two years, more than half of airports have been technically efficient. The rest showed inefficiencies. This was due to fewer passengers and a higher percentage of flight delays.

Ahn, Y.-H., & Min, H. (2014) did comparative measures of international airport performance from to 2006-2011 using encapsulation analysis for dynamic comparison and Malmquist's yield index under time-series analysis. This study indicates that airport efficiency is influenced by external factors, such as changes in government policy and technological advancements, rather than external factors driven by improvements in management practices.

Ennen and Batool (2018) studied the efficiency of an airport in Pakistan using data framing analysis to measure the efficiency of 12 major airports. In this study, the input variables consisted of the number of take-off and landing routes, the number of runways of the aircraft, the size of the terminal, the number of employees, and the export factors consisted of the number of flights of domestic passengers of international passengers; the total number of passengers of goods delivered by this study found that there was a cost inefficiency at almost every airport, and the scale of operations at almost all airports is a little inefficient.

Corrado (2018) studied the technical performance, cost, and profitability of Italian airports. This study used imported variables consisting of the dimensions of the terminal aircraft yard size, length of boarding and disembarkation, number of employees, operating expenses, labour costs, and export factors, including the number of passengers. The study finds that privately operated airports are more efficient than government-run airports.

Fragoudaki and Giokas (2016) studied the efficiency of airports in countries open to tourists. A case study of Greece. The inputs are defined as follows: length of the boarding and landing routes, size of the airfield, and size of the terminals. The output factors include the number of passengers, flights, and goods. This study suggests a scope for improving Greece's airport efficiency. It was also found that the location of the airport, connections to transportation, hotels and other infrastructure around the airport significantly affects the efficiency of the airport.

Table 1: Input used and output produced under the Data Envelopment Analysis (DEA).

Authors	Method	Analysis Target	Input	Output
Liu, 2016	Network DEA	10 East Asian airports	(1) runway area (2)sta costs (3) other operating costs	(1) passengers and cargo (2) operating revenues
Carlucci, et al. 2018	DEA	34 Italian airports	(1) labor costs (2) invested capital (3) other expenses	(1) passenger movement (2) cargo (3) aircraft movements (4) revenue

Zou, B. et al. 2015	Two-staged DEA	42 primary US airports	(1) labor cost (2) materials cost (3) capital cost	(1) passenger enplanements(2) cargo (3)aircraft operations (4) non-aeronautical revenue (5) delay
Lozano and Gutierrez (2011)	SBM DEA	39 Spanish airports	Total runway area Apron capacity Num. of baggage belts Num. of check-in counters Num. of boarding gates	Annual passenger movements, aircraft traffic movements and cargo handled
Gitto and Mancuso (2012)	DEA + bootstrapping + MPI	28 Italian airports	Labor cost, capital invested, soft costs	Number of movements (aircraft landing and taking off) and number of passengers
Ahn and Min (2014)	DEA + MPI	23 international airports	Land area, number of runway units, passenger, terminal area, and cargo terminal area	Number of flights, annual passenger throughputs, and annual cargo throughputs
Lo Storto Corrado (2018)	DEA meta-frontier	45 Italian airports	terminal size, apron size, Length of takeoff and landing, number of employees, operating costs, labor cost	number of passengers labor cost airport operating profit
Fragoudaki and Giokas (2016)	DEA Bootstrap+ Tobit regression	38 Greek airports	length of takeoff and landing, apron size, size of the terminal	number of passengers, number of flights, cargo

Source: From literature review

Methodology

To measure the operational efficiency of all eight airports, research data from two sources were used: primary data obtained from airport users through surveys and secondary data obtained from the annual data collection of the Airport Department and Airports of Thailand Public Company Limited. Using the SBM-DEA model, the 5-year operational performance of the eight airports is measured, with the context of SBM-DEA model assuming DMUj (x_(o,) y_o) as the performance of the SBM-DEA model as a set of decision-making units (DMU) by J = {1,2,...,n}, where each DMU has m as an input and s as an output. This study reveals the vectors of DMUj inputs and outputs, assigning xj = (x1j,x2j,...,xmj)T and giving yj = (y1j,y2j,...,ysj)T. Furthermore, this study determines the input and output factor metrics in the form of X and Y by

$$X = (x_1, x_2, \dots x_n) \in R^{mxn} \text{ and } Y = (y_1, y_2, \dots y_n) \in R^{sxn} \qquad (1)$$

According to the relevant performance of DMUj $(x_{o,} y_o)$allowing $P_l = 1$ where the shortage of inputs is zero $S^- = 0$ and

The shortage of export may not be zero S^+=0 This study solves the problem with a linear equation method, so the data framework of the inputs of the SBM model under Constant return to scale (CRS) is shown as follows.

$$P_l = \min 1 - \frac{1}{m} \sum_{i=1}^{m} \frac{s_i^-}{x_{io}}$$

where,

$$x_{io} = \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- \;\; (i = 1, \dots, m),$$

$$y_{ro} = \sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ \;\; (r = 1, \dots, s),$$

$$\lambda_j \geq 0, s_j^- \geq 0, s_r^+ \geq 0 \qquad (2)$$

This study presents the SBM baseline modality under the DMU hypothesis of 1 on the basis of variable return to scale (VRS) as being used under incomplete competitive conditions within the market, so the hypothesis of the data defined positively by X > 0, and Y > 0. After that, the production capability set under the VRS model can be defined as follows.

$$P_{VRS} = \left\{ (x,y) | \; x \geq \sum_{j=1}^{n} x_j \lambda_j, 0 \leq y \leq \sum_{j=1}^{n} y_j \, \lambda_j, \sum\nolimits_{j=1}^{n} \lambda_j = 1, \lambda \geq 1 \right\} \quad (3)$$

$\lambda = (\lambda_1, \lambda_2, \ldots \lambda_n)^T$ is defined as the intensity vector. Thus, the output boundary of the SBM model under variable return to scale (VRS) has been created, and shown as follows.

$$P_I^* = \min 1 - \frac{1}{m} \sum_{i=1}^{m} \frac{s_i^-}{x_{io}}$$

where

$$x_{io} = \sum_{j=1}^{n} x_{ij} \lambda_j + s_i^- \;\; (i = 1, \ldots, m),$$

$$y_{ro} = \sum_{j=1}^{n} y_{rj} \lambda_j - s_r^+ \;\; (r = 1, \ldots, s),$$

$$\sum\nolimits_{j=1}^{n} \lambda_j = 1,$$

$$\lambda_j \geq 0, s_j^- \geq 0, s_r^+ \geq 0 \qquad (4)$$

The study uses VRS model conditions to align with the actual circumstances and operations of the eight airports. According to model 4, where the VRS model is the terminology of data framework analysis in the Scarcity Measurement Model (SBM-DEA), which is described by

$\sum_1^N \lambda_n = 1$ (Banker et al, 1984).

Tobit regression’s model

The Tobit regression model, invented by James Tobin in in 1958, is suitable for continuous variable values, but there may be some missing values and cannot be measured, or variables based on continuous variable values, but some values of missing variables cannot be measured. Therefore, the regression model was called the Censored Regression Model, which was later referred to as the Tobit model after the inventor's name. The equation can be written as follows:

$$Y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + ... + \beta_k x_{ki} + \varepsilon_i , i = 1,..., n \qquad (5)$$

Yi is a variable based on x_{1i}, x_{2i}, …., x_{ki} is the 1st independent variable up to the one at k.

β is, Unknown regression coefficient

εi is a random discrepancy and $\varepsilon_i \sim_{i.i.d.N} (0, \sigma^2)$.

Scope of research

The population in this study consists of eight airports comprising of airports within Ranong, Phuket, Krabi, Trang, Chumphon, Surat Thani, Nakhon Si Thammarat and Songkhla Province.

Data Collection

Primary data were obtained from the collection of survey data using open-ended questionnaires with stakeholders in airport management and operation. The quota set for each airport was 50 respondents and 400 samples were used in this study. The sample size for Taro Yamane was at the 95% confidence level (Yamane, 1973). Secondary data is obtained from the collection of annual operations of the eight airports in southern Thailand from 2017 to 2019.

Variables used in the study

From the above literature review, the variables used in this study were independent variables, which consisted of the number of check-in counters, terminal area, number of runways, parking area lots and pit stops and dependent variables, including number of passengers, number of flights, and number of goods.

Results

This study measured the three-year efficiency and operational capability from 2017-2019. This is based on the efficiency and operational capability of the eight airports in southern Thailand. The results show that the correlation of the variables used in the performance analysis ranges from -1.0 to +1.0, as shown in Table 2. The input includes the number of check-in counters, terminal area, parking areas lots and pits. When considering relationships with other variables, it was close to 1, which means that the variables mentioned above and the other variables show many correlations in the same direction. The number of runway variables was set to 0. When considering the relationships with other variables, it was found that the number of runway variables and other variables did not correlate. In terms of the output factor, the number of passengers and flights approaches one when the relationship with other variables is considered. This means that the abovementioned variables strongly correlate with other variables. In addition, there is only one output factor: the number of products that is less than zero. This means that the number of product variables and other variables has a strong correlation oppositely. From Table 3, it was found that the efficiency and operational capabilities of the eight airports in the southern region of Thailand can be classified in order of efficiency and inefficiencies as follows:

Table 2: The correlation of input and output variables.

Input and output variables	Number of check-in counters	Terminal Area	Number of Runways	Parking area lots and pit stops	Number of passengers	Number of flights	Number of goods
Airport Counter Check-in	1	0.976265	0	0.992663	0.9880077	0.984116	-0.123223
Terminal Area	0.976265	1	0	0.979165	0.993986	0.987658	-0.132163
Number of Runways	0	0	1	0	0	0	0
Apron	0.992663	0.979165	0	1	0.9862991	0.982628	-0.204453
Passengers Volume	0.988008	0.993986	0	0.986299	1	0.997728	-0.125651
Air Traffic	0.984116	0.987658	0	0.982628	0.9977275	1	-0.112945
Freight and Mail	-0.123223	-0.132163	0	-0.204453	-0.125651	-0.112945	1

Source: calculated

Table 3: Efficiency and operational capability of the eight airports in southern Thailand.

Order	Airport	Efficiency Scale
1.	Ranong (UNN)	1.00
2.	Chumphon (CJM)	0.84
3.	Krabi (KBV)	0.96
4.	Phuket (HKT)	0.98
5.	Surat Thani (URT)	0.95
6.	Nakhon Si Thammarat (NST)	0.99
7.	Trang (TST)	1.00
8.	Hat Yai (HDY)	0.91

Table 4: A total of 24 DMUs, sequences, scores, and reference sets.

No.	DMU	Score	Rank	Reference set		
1	Ranong (UNN)*	1	1	Ranong (UNN)*		
2	Chumphon (CJM)*	0.838	21	Ranong (UNN)*		
3	Krabi (KBV)*	0.993	14	Nakhon Si Thammarat (NST)*	Krabi (KBV)**	Phuket (HKT)**
4	Phuket (HKT)*	0.944	17	Nakhon Si Thammarat (NST)*	Phuket (HKT)**	
5	Surat Thani (URT)*	1	1	Surat Thani (URT)*		
6	Nakhon Si Thammarat (NST)*	1	1	Nakhon Si Thammarat (NST)*		
7	Trang (TST)*	1	1	Trang (TST)*		
8	Hat Yai (HDY)*	1	1	Hat Yai (HDY)*		
9	Ranong (UNN)**	1	1	Ranong (UNN)**		
10	Chumphon (CJM)**	0.838	21	Ranong (UNN)*	Ranong (UNN)**	
11	Krabi (KBV)**	1	1	Krabi (KBV)**		
12	Phuket (HKT)**	1	1	Phuket (HKT)**		
13	Surat Thani (URT)**	1	1	Surat Thani (URT)**		
14	Nakhon Si Thammarat (NST)**	0.989	15	Nakhon Si Thammarat (NST)*	Trang (TST)*	
15	Trang (TST)**	1	1	Trang (TST)**		
16	Hat Yai (HDY)**	0.930	18	Nakhon Si Thammarat (NST)*	Hat Yai (HDY)*	Phuket (HKT)**
17	Ranong (UNN)***	1	1	Ranong (UNN)***		
18	Chumphon (CJM)***	0.838	21	Ranong (UNN)*	Ranong (UNN)***	
19	Krabi (KBV)***	0.878	19	Nakhon Si Thammarat (NST)*	Krabi (KBV)**	Phuket (HKT)**
20	Phuket (HKT)***	0.995	13	Nakhon Si Thammarat (NST)*	Phuket (HKT)**	
21	Surat Thani (URT)***	0.847	20	Nakhon Si Thammarat (NST)*	Phuket (HKT)**	
22	Nakhon Si Thammarat (NST)***	0.984	16	Nakhon Si Thammarat (NST)*	Trang (TST)*	
23	Trang (TST)***	1	1	Trang (TST)*		
24	Hat Yai (HDY)***	0.793	24	Nakhon Si Thammarat (NST)*	Phuket (HKT)**	

Source: calculated

Table 5: Excess input and output data, the deficiencies of decision-making units (DMU) running out of 24 DMUs.

No.	DMU	Excess Airport Counter Check-in S-(1)	Excess Terminal Area S-(2)	Excess Number of Runways S-(3)	Excess Apron S-(4)	Shortage Passengers Volume S+(1)	Shortage Air Traffic S+(2)	Shortage Freight and Mail S+(3)
1	Ranong (UNN)*	0	4.00E-02	1.00E-05	3.00E-05	0	0	0
2	Chumphon (CJM)*	1.00004	3200.04	0	0	33522.79	123.9839	0
3	Krabi (KBV)*	0.371539	334.65522	0	5.18E-03	0	583.5477	0
4	Phuket (HKT)*	6.048933	8014.0905	1.00E-05	2.779229	0	3998.348	70052.58
5	Surat Thani (URT)*	0	0	0	0	0	0	0
6	Nakhon Si Thammarat (NST)*	0	0	0	0	0	0	0
7	Trang (TST)*	0	0	0	0	0	0	0
8	Hat Yai (HDY)*	0	0	0	0	0	0	0
9	Ranong (UNN)**	0	0	1.00E-05	0	0	0	1.250453
10	Chumphon (CJM)**	1.00004	3200.04	0	0	9410.886	0	0
11	Krabi (KBV)**	0	0	0	0	0	0	0
12	Phuket (HKT)**	0	0	0	0	0	0	0
13	Surat Thani (URT)**	0	0	0	0	0	0	0
14	Nakhon Si Thammarat (NST)**	0	106.37535	0	8.86E-02	0	181.1013	268206.2
15	Trang (TST)**	1.10E-04	3.00E-02	1.00E-05	2.00E-05	0	0	6.6946
16	Hat Yai (HDY)**	4.471324	0	0	2.221264	0	2209.653	271402.6
17	Ranong (UNN)***	0	0	0	0	0	0	1.349229
18	Chumphon (CJM)***	1.00004	3200.04	0	0	2977.546	0	0
19	Krabi (KBV)***	4.680746	5284.065	0	1.186617	0	4812.733	0
20	Phuket (HKT)***	0.458628	607.54068	0	0.21071	0	2083.11	11317.13
21	Surat Thani (URT)***	1.349201	6608.7783	0	0.241514	0	7963.703	201731.9
22	Nakhon Si Thammarat (NST)***	0	160.33576	0	0.133608	0	1942.435	221416.6
23	Trang (TST)***	0	0	0	0	119971	795.9482	104233.9
24	Hat Yai (HDY)***	12.38784	1060.944	1.00E-05	6.124132	0	6570.964	707235.5

Source: calculated

The Ranong (UNN) and Trang (TST) airports have had the highest efficiency and operational capability in the last three years. This was followed by Nakhon Si Thammarat Airport (NST), Phuket (HKT), Krabi (KBV), Surat Thani (URT), Hat Yai (HDY) and Chumphon Airport () with performance values of 1, 0.99, 0.98, 0.96, 0.95, 0.91, and 0.84, respectively. Chumphon Airport (CJM) was the most inefficient. In addition, this study measured the efficiency and operational capabilities of eight airports in southern Thailand. The Decision Unit (DMU) was defined as having a total of 24 DMUs, with each airport being able to classify three DMUs, as shown in Table 4. Based on Table 4, a set of references or datasets used as benchmarks for airports looking to improve operational efficiency found that the airport most commonly used as a benchmark was Nakhon Si Thammarat Airport (NST)* in the year of operation in 2017, with nine reference frequencies, followed by Phuket (HKT)** in the year of operation 2018 with seven reference frequencies and Ranong (UNN)*, Trang (TST)*In the operating year 2017, the frequency of reference was three times.

The aforementioned airport information is presented in Table 5. The input and output factors remained the same. Therefore, it can be used as a benchmark for airports to improve their operational efficiency. The model determines the excess inputs and output factors based on the operational performance analysis methods of the eight airports under the SBM analysis technique. The data shown in Table 5 provide an idea of the number of inputs or outputs that should be increased or reduced. Considering the operating phase of the eight airports, their operations will require revision of almost all inputs and output factors except Ranong (UNN)*** In the year of operation 2019, no inputs and exits need to be improved or changed, for example, Hat Yai Airport (HDY)*** in the year of operation, 2019 must be improved by reducing input factors, such as; number of check-in counters should be reduced by 12.387 check-in counters, terminal area should be reduced by 1060.944 square meters, number of runways should maintain the level of the airport stable, excess parking area lots and pit stops should be reduced by 6.12. In addition, number of flights should increase by 6570,963 flights, and number of goods should increase by 707,235.4654 pieces.

Table 6. The results of the study showed the operational efficiency of the eight airports in Southern Thailand.

Variable	Coefficient	P-value	Mean of X
Airport Staff (X1)	0.23034711	0.0814*	4.37750000
Equipment & Facilities (X2)	-0.09312501	0.7473	3.97625000

Security (X3)	0.71702228	0.0148**	4.24250000
Airport Conditions (X4)	-0.65902204	0.0028***	4.14000000

Source: calculated

Note - * ** and *** refers to statistically significant at confidence levels of 90, 95 and 99, respectively.

The study's results on the relationship of factors that are expected to influence the change in operational efficiency of all eight airports in the southern region of Thailand with Tobit Regression Analysis, as shown in Table 6, show that there were three factors with acceptable statistical significance. Only the x3 security variable cannot explain the change in performance level at a statistically significant level; the airport staff factor variable (X1) had a variable coefficient (δ1) equal to 0.23034711, which was greater than 0 and had a different value. This was statistically significantly different from zero at a confidence level of 90 percent, which could be explained. Suppose all eight airports have employees at the airport (X1); the increase will result in an increase in the efficiency of the airport's operations or explain that when the number of airport staff (X1) increases by one unit, airport operating efficiency will increase by 0.23034711 units. The safety factor variable (X3) has a coefficient of variable (δ3) equal to 0.71702228, which is greater than 0 and statistically significantly different from zero at the 95 percent confidence level, which can be explained. If all eight airports had an increase in safety (X3), the airport's operating efficiency would increase. Safety (X3) increases by one unit, and airport operating efficiency increases by 0.71702228 units. The factor variable Airport condition (X4) has a coefficient of variable (δ4) equal to 0.71702228, which is less than zero and is statistically significantly different from zero at the 99% confidence level. This can be described as all eight airports having an increase in the number of airport conditions (X4), which would decrease the efficiency of the airport's operations. Airport condition (X4) increases by 1 unit, airport operating efficiency will decrease by -0.65902204 units.

Discussion and Conclusions

Passenger travel and air freight have constantly been expanding for more than ten years because of significant infrastructure improvements in the country, especially in the transport sector, whether by water, land, or air. Thailand has the policy to support the tourism industry and services to help bring more income to the country. As a result, the number of Thai and foreign tourists has continued to increase every year. The growth rate increases almost every year, especially in the southern region of Thailand. In addition to geography, the south has islands, mountains, and seas and is far from the capital, where it is located or the center of transportation. Therefore, air transport is essential because it is more convenient and faster than the other modes. Hence, it is popular among domestic and foreign tourists when they want to come to the south.

On the other hand, the increasing use of services by people in the provinces and neighboring areas has caused inefficiencies in operating the service management system. The construction and expansion of infrastructure projects need to be revised to meet service users' needs. Therefore, the study measuring the efficiency and operational capability of airports in the southern region of Thailand is given to all eight airports and determine limiting resource allocation within the airports of each province to achieve highest operational efficiency and also improve each (Decision-Making Unit: DMU) using the best decision-making unit as a baseline for inefficient DMUs. Moreover, this study identifies key factors that affect the efficiency of airport which regarding operations and management. The data analysis using the SBM-DEA method found that the Ranong (UNN) and Trang (TST) airports had the highest efficiency and operational capability or best practices in terms of operation and management. The mean efficiency was 1 using data from 2017-2019 for three years when considering Nakhon Si Thammarat (NST), Phuket (HKT), Krabi (KBV), Surat Thani (URT), and Hat. Yai (HDY) and Chumphon Airport (CJM) found that the operations were still inefficient. Most input factors should be improved, including number of check-in counters, terminal area and parking area lots and pit stops. The output factors are number of flights and. number of goods. Chumphon Airport (CJM) and Hat Yai Airport (HDY) are the least efficient. There should be a significant improvement in operational efficiency.

In addition, the study of factors affecting the operational efficiency of all eight airports in the southern region of Thailand using the Tobit regression analysis method found that the factor variables, airport condition (X4), have a coefficient of less than 0. Further, a statistically significant difference from zero at a 99 percent confidence level. If the number of airport conditions (X4) increases by one unit, it decreases the airport operating efficiency by of-0.65902204 units. The safety factor variable (X3) has a value coefficient greater than 0 and a statistically significant difference from zero at the 95 percent confidence level; if the number of safety (X3) increases by one unit, it will result in an increase in the operational efficiency of the airport by 0.71702228 units. The airport employee factor variable (X1) had a coefficient greater than 0 and a statistically significant difference from zero at the percentage confidence level of 90; if there is the amount of Airport staff (X1) increased by one unit, it will increase to 0.23034711 units in the airport's operational efficiency. Factors affecting the operating efficiency of all eight airports in the southern region of Thailand Sort by Airport condition (X4), security (X3), and airport staff (X1), respectively.

Nowadays, low-cost carriers have expanded exponentially to all over the world, because of the low-cost carrier business model can greatly reduce travel costs for passengers. In contrast, the service of low-cost carriers still maintains the same quality as leading airlines. The expansion of low-cost carriers has a direct impact on both domestic and international airport services. The airports must facilitate passengers who will use the services within the airports and will have to take care in regards to cleanliness and safety of passengers who come to use the service within the terminal building. The airports must prepare a place for sitting, restrooms, food court, luggage storage, exit lane for airplane and number of runways and other services such as vending machines, restaurants and cafes must be prepared to meet the needs of passengers who come to use the airport service before departure. In addition, airports should pay attention to checkpoints to monitor passenger safety and have collaborating with security agencies to exchange real-time information and maintaining the standards of various equipment to be ready to use and safe such as passenger elevators in the building, escalators, CCTV inside and outside the building, electrical system, water supply system, conveyor system, vehicle system and other equipment etc.

This research can create appropriate input and output factors for the environment of airport operations in the southern region of Thailand which consists of the number of check-in counters, terminal area, number of runways, parking area lots and pit stops, number of passengers, number of flights, and number of goods. It also has prototype airports that can be used as benchmarks for reference and improvement for airports in the southern region and airports in other areas of Thailand as well. The business model of airport consists of Ranong (UNN), Trang (TST), Nakhon Si Thammarat (NST) and Phuket (HKT). In addition, the results of the research are able to identify key factors that affect the efficiency of airport operations and management within the southern region of Thailand which can be prioritized as follows Airport condition (X4), security (X3), and airport staff (X1), respectively. In addition, technical efficiency is a very influential quantitative measure tool. Because it is used to measure efficiency in a variety of industries. Its technical efficiency is commonly used to measure operations within airports around the world. Any airport that uses innovation or new technology to facilitate and reduce operational time from responsible work. Those airports will receive a high level of satisfaction and when have measuring efficiency, they will be at a high level as well.

Therefore, the eight airports in the southern region of Thailand should adopt the criteria from the above research as a business model for airports, they can setup a new framework and guideline to drive their policies within the organization and also to strengthen competitiveness by setting strategies from innovation or technology. The reason come from innovation or technology can make a difference in service over competitors and a good impression on passengers who come to use the airport service.

Limitation and recommendation

Collecting the questionnaire is not able to collect all data of all flights. There are some limitations in accessing the data at certain times. In the next research, questionnaire will be designed to be able to do online test by scanning QR code which can be collected data on every flight.

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Bibliography

Ahn, Y.-H., & Min, H. (2014). Evaluating the multi-period operating efficiency of international airports using data envelopment analysis and the Malmquist productivity index. Journal of Air Transport Management, 39, 12-22. doi:https://doi.org/10.1016/j.jairtraman.2014.03.005

Annual Operations Report of the Airport Department 2560. Department of Airports Ministry of Transport

Banker, R.D., Charnes, A. & Cooper, W.W. (1984). Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. Management Science, 30(9), 1078–92.

Carlucci, F., Cirà, A., & Coccorese, P. (2018). Measuring and Explaining Airport Efficiency and Sustainability: Evidence from Italy. Sustainability, 10(2). doi:10.3390/su10020400

Changa. Y., Park. H., Jeong. J and Lee. J. (2014) "Evaluating economic and environmental efficiency of global airlines: A SBM-DEA approach." Transportation Research Part D: Transport and Environment 27: 46-50.

Choi, Y., Wen, H., Lee, H., & Yang, H. (2020). Measuring Operational Performance of Major Chinese Airports Based on SBM-DEA. Sustainability, 12(19). doi: 10.3390/su12198234

Curi, C., Gitto, S., & Mancuso, P. (2010). The Italian airport industry in transition: a performance analysis. Journal of Air Transport Management, 16(4), 218-221. doi:https://doi.org/10.1016/j.jairtraman.2009.11.001

Dalei, N. N., & Joshi, J. M. (2020). Estimating technical efficiency of petroleum refineries using DEA and tobit model: An India perspective. Computers & Chemical Engineering, 142, 107047. doi: https://doi.org/10.1016/j.compchemeng.2020.107047

Debreu, G. (1951). The coefficient of resource utilization. Econometrica, 19(3): 273–292.

Deng, G., Li, L., and Song, Y. (2016). "Provincial water use efficiency measurement and factor analysis in China: Based on SBM-DEA model." Ecological Indicators 69: 12-18.

Ennen, D., and Batool, I. (2018). Airport efficiency in Pakistan - A Data Envelopment Analysis with weight restrictions. Journal of Air Transport Management, 69, 205-212.

Farrell MJ. (1957) The measurement of production efficiency. Journal of Royal Statistical Society, 120, 253-290.

Fragoudaki, A. and D. Giokas (2016). "Airport performance in a tourism receiving country: Evidence from Greece." Journal of Air Transport Management 52: 80-89.

Gitto, S., & Mancuso, P. (2012). Bootstrapping the Malmquist indexes for Italian airports. International Journal of Production Economics, 135(1), 403-411. doi:https://doi.org/10.1016/j.ijpe.2011.08.014

Huynh, T. M., Kim, G., & Ha, H.-K. (2020). Comparative analysis of efficiency for major Southeast Asia airports: A two-stage approach. Journal of Air Transport Management, 89, 101898. doi: https://doi.org/10.1016/j.jairtraman.2020.101898

lo Storto, C. (2018). "Ownership structure and the technical, cost, and revenue efficiency of Italian airports." Utilities Policy 50: 175-193.

Koopmans T. (1951) Activity analysis of production and allocation. John Wiley & Sons, New York.

Lee, H., Choi, Y., Yang, F., & Debbarma, J. (2021). The governance of airports in the sustainable local economic development. Sustainable Cities and Society, 74, 103235. doi: https://doi.org/10.1016/j.scs.2021.103235

Lee, T., Yeo, G, T., and Thai, V, V. (2014). "Environmental efficiency analysis of port cities: Slacks-based measure data envelopment analysis approach." Transport Policy 33: 82-88.

Lozano, S., & Gutiérrez, E. (2011). Slacks-based measure of efficiency of airports with airplanes delays as undesirable outputs. Computers & Operations Research, 38(1), 131-139.

Sergi, S. B., D’Aleo, V., Arbolino, R., Carlucci, F., Barilla, D., & Ioppolo, G. (2020). Evaluation of the Italian transport infrastructures: A technical and economic efficiency analysis. Land Use Policy, 99, 104961. doi: https://doi.org/10.1016/j.landusepol.2020.104961

Song, M., Wang, R., & Zeng, X. (2018). Water resources utilization efficiency and influence factors under environmental restrictions. Journal of Cleaner Production, 184, 611-621. doi: https://doi.org/10.1016/j.jclepro.2018.02.259

Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis, European Journal of Operational Research, 498-509

Tsui, W. H. K., Gilbey, A., & Balli, H. O. (2014). Estimating airport efficiency of New Zealand airports. Journal of Air Transport Management, 35, 78-86. doi: https://doi.org/10.1016/j.jairtraman.2013.11.011

Taro Yamane (1973). Statistics: An Introductory Analysis.3rdEd.New York.Harper and Row

Publications.

Wang, L., Zhou, Z., Yang, Y., & Wu, J. (2020). Green efficiency evaluation and improvement of Chinese ports: A cross-efficiency model. Transportation Research Part D: Transport and Environment, 88, 102590. doi: https://doi.org/10.1016/j.trd.2020.102590

Yu, M.-M. (2010). Assessment of airport performance using the SBM-NDEA model. Omega, 38(6), 440-452. doi:https://doi.org/10.1016/j.omega.2009.11.003

Zou, B., Kafle, N., Chang, Y.-T., & Park, K. (2015). US airport financial reform and its implications for airport efficiency: An exploratory investigation. Journal of Air Transport Management, 47, 66-78. doi:https://doi.org/10.1016/j.jairtraman.2015.05.002