OPERATIONAL EFFICIENCY MEASUREMENT AT SELECTED AIRPORTS*

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ABSTRACT

With the development of air transport, the capacity of airports increasing in use day by day is insufficient. Therefore, it has been thought that airports should be used effectively and efficiently. A number of studies have been conducted by airport managers and competent authorities to improve effectively and efficiently in airports. Many performance measurement methods are used in these studies. Data Envelopment Analysis (DEA), where many input and output variables are used, is one of the most widely used performance measurement methods in airports.

In the first part of this study, the importance of performance measurement at airports is mentioned. In the second part, the previous studies with the DEA in the airports were researched. In the third part, information about the DEA was given. In the last part, operational efficiency measurement of 20 airports which can be accessed within the first 25 airports of the world in terms of number of passengers was done with DEA. In the analysis phase, input variables such as runway number, aircraft number, gate number and terminal area size are used. Total number of flights, total freight and total number of passengers were used as output variables. In the conclusion section, suggestions for ineffective airports are presented.

Keywords: *Airport Perfomance, Efficiency, Productivity, DEA.*

SEÇİLMIŞ HAVALİMANLARINDA OPERASYONEL ETKİNLİK ÖLÇÜMÜ

ÖZET

Hava taşımacılığının gelişmesi ile birlikte kullanımı her geçen gün artan havalimanlarının zamanla mevcut kapasiteleri yetersiz kalmaktadır. Bundan dolayı havalimanlarının etkin ve verimli bir şekilde kullanılması gerektiği düşünülmüştür. Havalimanlarındaki etkinlik ve verimliliğin arttırılması için havalimanı yöneticileri ve yetkili otoriteler tarafından birçok çalışma yapılmaktadır. Bu çalışmalarda birçok performans ölçüm yöntemleri kullanılmaktadır. Birçok girdi ve çıktı değişkenin kullanıldığı Veri Zarflama Analizi (VZA) havalimanlarında en yaygın kullanılan performans ölçüm yöntemlerinden biridir.

Bu çalışmanın birinci kısmında havalimanlarında performans ölçümünün önemine değinilmiştir. İkinci kısımda havalimanlarında VZA ile yapılmış önceki çalışmalar araştırılmıştır. Üçüncü bölümde VZA hakkında bilgi verilmiştir. Son bölümde ise yolcu sayısı açısından dünyanın ilk 25 havalimanı içerisinde verilerine ulaşılabilen 20 havalimanın operasyonel etkinlik ölçümü VZA ile yapılmıştır. Analiz aşamasında pist sayısı, uçak park sayısı, kapı sayısı ile terminal alanı büyüklüğü gibi girdi değişkenleri kullanılmıştır. Çıktı değişkenleri olarak toplam uçuş sayısı, toplam yük miktarı ile toplam yolcu sayısı kullanılmıştır. Sonuç bölümünde ise etkin olmayan havalimanları için öneriler sunulmuştur.

Anahtar Kelimeler: *Havaalanı Performans, Etkinlik, Verimlilik, VZA.*

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1. Introduction

The rapid development of technology results in shortening of distances, increasing communication and globalization, facilitating transportation, and, most importantly, increasing competition in the world markets. However, this also brings out an emerging need for using scarce resources in the world effectively and efficiently. Businesses operating in the production and service sectors need performance measurement systems to benchmark their current situation, to be able to compare themselves to market competitors, to keep pace with changing market conditions and to make future business plans.

To measure their efficiency and effectiveness, businesses first used the ratio analysis of a single input to a single output. However, over time, with the use of many inputs and outputs in businesses, the ratio analysis has become insufficient. Subsequently, parameterized methods, in which many inputs are proportioned to a single output, have begun to be used. Over time, however, this method was also ineffective, and mathematical programming-based measurement methods without parameters have begun to be used, in which many inputs can be scaled to many outputs. The most commonly used method among non-parametric measurement methods is data envelopment analysis (DEA). Although the application of DEA seems difficult, the software programs enabled by the more advanced technology have made it easier to apply.

2. Performance Measurement at Airports

Due to the developments experienced in the air transport sector in recent years, there has been a great change in terms of management approach at the airports. Measuring the operational and financial performance of airports operated with a commercial or build-operate-transfer model becomes particularly important. In this respect, managers of airport operators feel the need to measure their efficiency and effectiveness for a number of reasons. These reasons are listed below (Doganis, 1992:158-159):

• Performance metrics are needed to determine where the airports economically are, to determine the indicators needed to measure financial performance, and how the airport manager is using the available resources. However, performance measurement is also carried out with the aim of comparing the efficiency of the different units in the airports.

• Performance measurement at airports allows airport managers to make the most appropriate decisions and can help them to take necessary precautions against unexpected changes. Furthermore, performance analysis at airports allows the comparison of the airport's current situation with other airports.

• With the reduction of state control over the airports, they are operated by commercial organizations and are becoming more successful in terms of efficiency and effectiveness. However, a number of indicators are needed to measure efficiency and effectiveness. Thus, performance analysis is very important in terms of helping the operator attain objectives and determine new targets.Lorem ipsum dolor sit amet, consectetur adipiscing elit. Ut rutrum nisi ut eleifend maximus. Sed quis felis a magna dignissim pellentesque sit amet at lorem. Morbi commodo accumsan orci, nec iaculis mi. Curabitur libero enim, iaculis eget lacus varius, pellentesque ornare turpis. Pellentesque lobortis volutpat lorem, sed iaculis quam. Suspendisse potenti. Suspendisse efficitur enim non est venenatis cursus. Bir alt bölümle arada bir satır boşluk bulunacak.

2.1. Studies on Performance Measurement in Airports

Numerous studies have been conducted using data envelope analysis techniques to search for the answer to the question whether airports, which are one of the most important elements of the aviation industry growing everyday with the development of technology in the world and in Turkey, are being used effectively. Some of these studies are cited below:

Gillen and Lall took the number of runways, the number of gates, the terminal area, the number of employees, the parking area and the number of luggage collection bands as inputs, and took the total number of passengers and flights, and total cargo volume as outputs to measure the effectiveness of 21 airports in the US after economic liberalization. As a result of this analysis they determined that privatized airports become more efficient (Gillen & Lall, 1997: 261).

In order to measure the efficiency of 44 airports in the US between 1990 and 1994, Sarkis used the number of runways, the number of gates, the number of employees and operation costs as inputs and used the total number of passengers and flights, operation and general aviation revenues, and the total amount of cargo as the output. As a result of the analysis, some suggestions were made explaining the necessary steps to take towards making the ineffective airports effective (Sarkis, 2000: 335).

To measure the efficiency of 37 airports in Spain prior to privatization, Martin and Roman used the number of employees, the amount of capital invested and the number of devices as the input, and the total number of passengers, flights and total load as the output. As a result of the analysis, it was determined that some airports were inefficient and some recommendations were made to enable such airports to become efficient (Martin &Roman, 2001: 149).

Developing a model to measure the efficiency of 26 airports, Adler and Brechman studied the relationship of factors influencing airport operators' hub selection with airport efficiency. Their analysis indicated that airports such as Milan, Munich and Genoa were efficient, but major airports such as Charles De Gaulle, Athens and Manchester were inefficient (Adler & Brechman, 2001: 171).

Fernandes and Pacheco attempted to measure the efficiency of 35 airports in Brazil using the BCC model of the DEA analysis. Factors such as the size of the airport, the number of ticket check-in counters, the size of the waiting room, the size of the parking area, and the size of the luggage area were considered as the inputs, and only the total number of passengers was taken as the output. Their analysis suggested that airport terminal capacity should be used more efficiently (Fernandes & Pacheco, 2002: 225).

Yoshida and Fujimoto measured the efficiency of 67 airports in Japan using DEA method. In the analysis, the number of the runways, the terminal area and the number of employees were considered as the inputs, and the total number of passengers and flights, and the total amount of cargo were taken as the output. As a result of the analysis, it was found that the airports in Japan were not efficient. It was also noted that some regional airports had undergone excessive investment (Yoshida and Fujimoto, 2004: 533).

Bazargan and Vasigh measured the efficiency of 45 airports classified as large, medium and small in the USA between 1996 and 2000, through the DEA. In the analysis, operation and non-operation expenditures, number of gates and number of runways were considered as the inputs, and the output was based on total number of passengers, commercial and non-commercial flights, aviation and non-aviation revenues. As a result of the analysis, the airports considered as big were found to be efficient (Bazargan & Vasigh, 2003: 187).

Yu measured the efficiency of 14 airports in Taiwan between 1994 and 2000 with an output-oriented DEA model and focused on the environmental impact of airports. For this purpose, the total length of the runway, the apron size, the terminal area, and the number of connected flights from each airport were taken as the input, and the total number of flights and passengers was taken as the output. In addition, the amount of noise generated by aircraft landing and departing was also considered as undesirable output. As a result of the analysis, it was reported that except for a few airports the airports were efficient (Yu, 2004: 295).

In order to measure the operational efficiency of 32 airports in Turkey between 1996 and 2002, Kıyıldı and Karaşahin used parking lot capacity, number of ticket control counters, number of x-ray devices, runway length, apron size and aircraft capacity as the inputs, and used the total number of flights as the only output. The results of the analysis revealed that a large number of the airports constructed by investing large amounts of public funds were not efficient (Kıyıldı &Karaşahin, 2006: 391).

With the aim of measuring the efficiency of 37 airports in Turkey in 2007, Peker and Baki used car park capacity, number of runways, airport size and number of employees as the input, and the total number of passengers and total load amount as the output. As a result of the analysis, it was reported that of the major airports, Atatürk, Antalya, Adana, Trabzon and Kayseri airports were efficient, and among the small airports, Malatya and Çardak airports were efficient (Peker & Baki, 2009: 72).

Ömürbek et al. classified 40 airports in Turkey as large, medium and small airports according to the number of passengers, and to measure their performance between the years of 2007 and 2010 They used car park, passenger and plane capacity, the number of data processing and rescue devices and number of personnel as the inputs, and the amount of total load and total number of passengers and flights as the output. As a result of the analysis, Dalaman Airport as one of the major airports and most of the medium and small sized airports were found not to be efficient (Ömürbek et al., 2013: 21).

Ülkü measured the efficiency of 73 airports operated by AENA in Spain and General Directorate of State Airports Authority in Turkey between the years 2009 and 2011 by data envelopment analysis. In the analyses process, personnel expenses, runway number and runway length were used as input variables. The total number of passengers and flights and the total amount of cargo carried are used as output variables. As a result of the analysis, it was determined that the airports in Spain are more effective than the airports in Turkey. Small airports in both countries have not been optimally effective (Ülkü, 2015: 56).

Fragoudaki and Giokas measured the efficiency of 38 airports by data envelopment analysis. Through the Tobit regression model, factors that affect the efficiency of the airports were tried to be estimated. Variables such as runway length, apron and terminal area are determined as input. The total amount of cargo and the total number of passengers and flights are considered as output variables. As a result of analysis, 11 airports were efficient and other airports were not efficient. (Fragoudaki & Giokas, 2016: 81)

Other studies on DEA are given in Table 1 below:

Table 1: Other Studies on Performance Measurement in Airports

Author / Year	Country	Sample	Method	Input	Output
Ülkü 2015	Turkey/Spain	73 Airports (2009-2011)	DEA	Staff Cost Number of Runway Total Runway Length	Total Number of Passengers Total Number of Fights Total Freight Commercial Revenues,
Karkacıer and Yazgan 2015	Turkey	37 Airports (2008-2011)	DEA	Number of Staff Operating Expenditures Terminal Area Number of Runway	Total Number of Passengers Total Number of Fights Total Freight
Lozano and Gutierrez 2011	Spain	41 Airports (2006)	DEA	Total Runway Length Apron Area Terminal Area Number of Check-in Desk Number of Gate	Total Number of Passengers Total Number of Fights Total Freight
Curi et al. 2011	Italy	18 Airports (2000-2004)	DEA	Number of Staff Number of Runway	Total Number of Passengers Total Number of Fights

				Apron Area	Total Freight
Koçak 2011	Turkey	40 Airports (2008)	DEA	Operating Expenditures Number of Staff Total Aircraft Movement	Total Number of Passengers Aircraft per Runway Total Freight Operating Revenue
Yu 2010	Taiwan	15 Airports (2006)	Slack Based DEA Model	Number of Staff Total Runway Length Apron Area Terminal Area	Total Number of Passengers Total Number of Fights Total Freight
Assaf 2010	UK	27 Airports (2007)	DEA	Number of Runway Total Airport Area	Total Number of Passengers Total Number of Fights Total Freight
Ablanedo-Rosas and Gemoets 2010	Mexico	37 Airports (2009)	DEA	Average number of Passengers Per Hour Average number of Flight Per Hour	Total Number of Passengers Total Number of Flights Total Freight
Lam, Low and Tang 2009	Asia-Pacific Region	11 Airports (2001-2005)	DEA	Number of Staff Amount of capital	Total Number of Passengers Total Number of Fights Total Freight

Chi-Lok and Zhang 2009	China	25 Airports (1995-2006)	DEA	Terminal Area Total Runway Length	Total Number of Passengers Total Number of Flights
Barros 2009	UK	27 Airports (2000-2006)	DEA	Staff Cost Operating Expenditures Amount of capital	Total Number of Passengers Total Number of Fights Total Freight Total Revenue
Yu et al. 2008	Taiwan	4 Airports (1995-1999)	DEA	Number of Staff Operating Expenditures	Total Number of Passengers
Barros 2008	Argentina	32 Airports (2003-2006)	DEA	Number of Staff Number of Runway Apron Area Terminal Area	Total Number of Passengers Total Number of Fights Total Freight
Barros and Dieke 2007	Italy	31 Airports (2001-2003)	DEA	Labor Cost Capital İnvested Operational Cost	Total Number of Passengers Total Number of Fights Total Freight Aviation Revenue Non Aviation Revenue
Martin and Roman (2006)	Spain	34 Airports (1997)	DEA	Labor Cost Capital Expenditures Material Expenditures	Total Number of Passengers Total Number of Fights Total Freight

Lin and Hong (2006)	Major Airports	20 Airports (2003)	DEA	Number of Staff Number of Check-in Desk Number of Runway Apron Area Terminal Area	Total Number of Passengers Total Number of Fights Total Freight
Sarkis and Talluri 2004	USA	44 Airports (1990-94)	DEA	Operational Cost Labor Cost Number of Gate Number of Runway	Total Number of Passengers Total Number of Fights Total Freight Operation Revenue
Pacheco and Fernansdes 2003	Brazil	35 Airports (1998)	DEA	Apron Area Total Lounge Area Number of Check-in Desk Parking area	Total Number of Passengers
Parker 1999	UK	32 Airports (1979/80-1995/96)	DEA	Number of Staff Operational Cost Capital Expenditures	Total Number of Passengers Total Freight

3. Data Envelopment Analysis

One of the non-parametric measurement methods, DEA, was introduced in 1957 with the work of Farel, inspired by the work of Cooper, Charnes and Rhodes (CCR), published in 1978, followed by the use of the model, now called CCR. In their study, Cooper and colleagues took the assumption of "constant returns to scale" basis.

Later, Banker, Cooper and Charnes based their assumptions on "variable return to scale", which is referred to as the BCC model in the literature. In BCC and CCR models, there are two different applications for both input and output. It is observed that the results of the studies conducted with DEA can be evaluated better due to its multiple types of applications (Yeşilyurt &Alan, 2003: 94).

DEA is a mathematical analysis method used in the measurement and evaluation stages of the activities of decision-making elements that are similar in terms of goods or services produced. Recently, it has been used extensively in management sciences and management research. (Kocakoç, 2003: 1). According to another definition, DEA is a linear programming based measurement method that helps measure the relative activities of units with multiple inputs and outputs operating in similar areas. DEA is the most widely used method in operational research, and can be easily applied in real life (Ulucan, 2002: 186-187).

Unlike other non-parametric measurement methods, DEA allows evaluation in the event of multiple inputs or outputs. By using DEA, it is possible to calculate the efficiency ratios of each determined decision unit, how to increase the efficiency of inefficient decision units, and which decision units to take as example (Yılmaz & Karakadılar, 2010: 506-507). DEA is an analytical method that has a complex structure and produces a solution with a small number of available data, unlike analysis methods that cannot fully express the input or output relationship (Cooper et al., 2011: 7). In addition, DEA has recently been used as a measure of efficiency and effectiveness in many different areas in various countries (Yılmaz & Karakadılar, 2010: 507).

DEA is a method used to measure financial or operational performance in production activities with multiple inputs and outputs where the regression analysis method cannot be directly applied. It is also an easy method to use when compared to other methods that do not allow many variables to be evaluated, which cannot be used together with many inputs and outputs that linear programming techniques cannot use, and which prevent the functioning of the decision-making mechanism (Akan & Çalmaşur, 201: 16-17).

3.1. Models Used in Data Envelopment Analysis

Models used in DEA can be categorized in different ways within themselves by taking different constraints as basis. Based on the assumption of "constant returns to scale", CCR models covering fractional and weighted envelope models for input and output were used during the first periods. Later, BCC models based on the assumption of "variable return to scale" began to be used. With the development of the DEA technique, however, many different models and different types of classification can be encountered today (Lovell & Pastor, 1997: 291).

3.1.1. CCR (Charnes, Cooper, Rhodes) Models

The CCR model is a model that is suitable for use in efficiency measurement of firms when operating at the optimum level (Tone, 2001: 32). However, the CCR model measures the effectiveness of decision-making elements, both individually and collectively, on the basis of constant return assumptions (Weng et al., 2009: 41), which is an output-oriented model that shows how much the outputs obtained from the analysis should be increased in order to make the decision-making unit effective with existing inputs without changing the input quantity (Matthews & Ismail, 2006: 7).

The mathematical notation of the output-driven CCR model is given below (Yolalan, 1993: 46):

$$Q_k = \max(\theta + \varepsilon \sum_{i=1}^{m} S_i^- + \varepsilon \sum_{r=1}^{s} S_r^+) \tag{1}$$

Constraints,

$$\sum_{j=1}^{n} X_{ij} \ \beta_j + S_i^- - X_{ik} = 0 \qquad i = 1, \ldots \ldots m \tag{2}$$

$$\sum_{j=1}^{n} Y_{rj} \ \beta_j - S_i^- - \beta \, Y_k = 0 \quad r = 1, \ldots .p \quad j = 1, \ldots n \quad i = 1, \ldots .m \tag{3}$$

$$\beta_j \geq 0 \qquad S_i^- \geq 0 \qquad S_r^+ \geq 0$$

In this model,

θ: is the expansion coefficient that determines how much the output of the decision unit is to be increased relative to the measured efficiency,

β(j): In the output-oriented models, the density value of the decision unit belonging to j,

CCR Effectiveness: In the first model, $\sum_{r=1}^{s} u_r\, y_{ro}$ means that the decision-making unit is effective when the objective function is equal to the value 1, and in other cases, the decision-making unit is not effective. The dual model assumes that the decision-making unit is effective when θ = 1 and S_i^- = 0, S_i^+ = 0 but the decision-making unit is considered ineffective in cases other than this (Yun et al., 2004: 89).

3.1.2. BCC (Banker, Charnes, Cooper) Models

$$Q_k = Min(\theta - \varepsilon \sum_{i=i}^{m} S_i^- - \varepsilon \sum_{r=1}^{p} S_r^+) \qquad (4)$$

Constraints,

$$\sum_{j=1}^{n} X_{ij}\ \beta_j + S_i^- - \theta X_{ik} = 0 \qquad i = 1,2, \dots m \qquad (5)$$

$$\sum_{j=1}^{n} X_{ij}\ \beta_j - S_i^+ - Y_{rk} = 0 \qquad r = 1,2, \dots p \qquad (6)$$

$$\sum_{j=1}^{n} \beta_j = 1 \qquad \beta_j \geq 0 \quad S_i^- \geq 0 \quad S_i^+ \geq 0 \quad j = 1,2, \dots n \quad i = 1,2 \dots . m \quad r = 1,2, \dots . p \qquad (7)$$

BCC Effectiveness: In the first model, $\sum_{r=1}^{s} u_r\, y_{ro} - u_o$means that the decision unit is effective when the objective function is equal to the value 1, and in cases other than this, the decision unit is not effective. The dual model is interpreted that the decision making unit is active when S_i^- = 0, S_i^+ = 0 with θ = 1, with θ = 1, and the decision making unit is ineffective in cases other than this (Banker et al., 2004: 347).

The mathematical presentation of the output-oriented envelopment model is given below (Gürgen & Norsworthy, 2001: 413):

$$E_o = Max(\theta + \varepsilon \sum_{i=i}^{m} S_i^- + \varepsilon \sum_{r=1}^{p} S_r^+) \qquad (8)$$

Constraints,

$$\sum_{j=1}^{n} X_{ij}\ \beta_j + S_i^- - X_{ik} = 0 \qquad i = 1,2, \dots m \qquad (9)$$

$$\sum_{j=1}^{n} y_{rj}\ \beta_j - \theta Y_{rk} - S_r^+ = 0 \qquad r = 1,2, \dots p \qquad (10)$$

$$\sum_{j=1}^{n} \beta_j = 1 \qquad \beta_j \geq 0 \quad S_i^- \geq 0 \quad S_i^+ \geq 0 \quad j = 1,2, \dots n \quad i = 1,2 \dots . m \quad r = 1,2, \dots . p \qquad (11)$$

4. Application

The first stage of the DEA used in the measurement of efficiency begins with the identification of decision units to be compared with each other. The homogeneity of the related units, that is, the observation clusters, is very important in terms of ensuring the reliability and significance of the analysis results. The homogeneity of the observation set means that the decision-making units that make up the observation set have the same input-output groups. In addition, the increase in the number of decision-making units causes the observation group to distort the homogenous structure and to include the unnecessary factors in the analysis. In this respect, decision-making units need to be carefully selected in order to ensure that efficiency measurement is reliable and meaningful (Yolalan, 1993: 89). From this point of view, the airports involved in the study are similar in terms of management, size and revenue. However, it can be argued that airports that represent research decision-making units (observation clusters) have a homogeneous structure in many respects.

Among the world's largest 25 airports by passenger traffic as ranked by the ACI (Airport Council International) in 2014, 20 airports in different parts of the world whose data could be accessed were included in the study. The data for Tokyo Airport, which is the fourth largest airport in the world, Guangzhou Airport ranking as the fifteenth, Kuala Lumpur airport ranked as the twentieth, and Seoul Airport ranking twenty-third in terms of their passenger traffic, could not be accessed and thus were excluded from the study. The fact that the airports involved in the research have similar inputs and outputs increases the reliability of the analysis to be applied.

A review of the relevant research carried out on the measurement of airport efficiency reveals two different views: Some of the studies that have been carried out argue that there is no effect of the relevant authority on the outputs that are included in the analysis but that it has an effect on the input amount and that the input-oriented data envelopment analysis model should be used (Bazargan & Vasigh, 2003; Yoshida & Fujimoto, 2004; 2006; Marques & Simons, 2010). Some other studies advocate an output-oriented data envelopment analysis model, claiming that output volume should be maximized (Sarkis, 2000; Martin & Roman, 2001; Barros & Dieke, 2008; Chi-Lok & Zang, 2009). There are, however, few studies that use both input and output-oriented models (Pacheco & Fernandes 2003). However, in most of the studies conducted based on the basic models of the DEA, the constant return based (CCR) model and the scale based variable return based (BCC) model were used. In this respect, in order to ensure that the efficiency measurement of the airports concerned can be carried out reliably and that the comparisons can be clearly demonstrated, the CCR model based on the constant return assumption and the BCC model based on the assumption of variable return to scale were used in this study. However, both the input-oriented DEA model and the output-oriented DEA model were used to compare the relevant airports in more detail.

In this study, the data of the four entry variables, including the number of runways, the number of airplanes, the number of gates and the size of the terminal area for related airports were included in the analysis. Included in the analysis were also the data on three output variables, including the total number of passengers, total load, and total number of flights for the respective airports. Thus, measuring the efficiency of operational airports in terms of operation is aimed.

The input variables such as the number of airplanes, the number of gates and the size of the terminal area were obtained from the internet sites of the relevant airports, master plans, reports issued by the competent authorities or by the authorities of the relevant airports by e-mail after the input and output variables of the relevant airports were determined. Output variables such as total number of passengers, total number of flights and total cargo volume were obtained from monthly Airline Business magazine. It was found that the Airline Business magazine obtains the data for the relevant airports from ACI (Airport Council International). Software that is used to solve problems based on mathematical programming is needed in order to enable efficiency measurement of related airports with DEA. Among these programs, DEA Frontier, DEAP, and Frontier Analyst are the most commonly used programs. Due to the high number of decision-making units, the use of the DEAP program was deemed appropriate for this study. In this study, the CCR model based on the constant returns to the scale assumption and the BCC model based on the variable return to scale assumption were used when the efficiency level of the related airports was calculated. However, data envelopment analysis models with input and output focus have been used to elaborate the analysis in more detail. In the analysis phase, the scale activity was first calculated with the CCR model of the relevant airports and then the technical efficiency was calculated with the BCC model. Efficiency values for the CCR, input and output oriented BCC models of the respective airports are given in Table 2.

Table 2: Efficiency Values of CCR, Input-Oriented and Output- Oriented BCC Models of Airports Included in the Analysis

Airport	*Efficiency Values of CCR*	*Input-Oriented BCC Models*	*Output- Oriented BCC Models*

Hartsfield- Jackson Atlanta	1.000	1.000	1.000
Beijing (Pekin)	0.965	1.000	1.000
Heathrow	1.000	1.000	1.000
Los Angeles	0.894	1.000	1.000
Dubai	1.000	1.000	1.000
Chicago O'Hare	0.749	1.000	1.000
Paris CDG	0.706	0.723	0.808
Dallas\ Fort Worth	0.609	0.746	0.832
Hong Kong	1.000	1.000	1.000
Frankfurt	1.000	1.000	1.000
Jakarta	1.000	1.000	1.000
Istanbul Atatürk	1.000	1.000	1.000
Amsterdam Schiphol	0.860	0.934	0.968
Singapur	0.771	0.809	0.810
Denver	0.587	0.671	0.794
New York JFK	1.000	1.000	1.000
Shanghai Pudong	1.000	1.000	1.000
San Francisco	0.850	0.905	0.876
Bangkok Suvarnabhumi	0.765	1.000	0.765
Charlotte Douglas	1.000	1.000	1.000

In DEA, a set of reference points are established by determining the decision-making units that need to be referenced by inefficient decision-making units. This reference set has been determined by the efficiency measurement through the DEAP software program. In this regard, the airports which should be referenced by the inefficient airports and the reference values of these airports are given in Table 3.

Table 3: Cluster of Inefficient Airports and Reference Values

CCR Model		***Input-Oriented BCC Models***		***Output- Oriented BCC Models***	
Inefficient Airports	Cluster of Reference Values	Inefficient Airports	Cluster of Reference Values	Inefficient Airports	Cluster of Reference Values
Beijing	Jakarta (1.043)	Beijing		Beijing	

	Hong Kong (0.162)				
	Heathrow (0.295)				
Los Angeles	Charlotte Douglas (0.315)	Los Angeles		Los Angeles	
	Hong Kong (0.280)				
	Jakarta (1.089)				
Chicago O’Hare	Hong Kong (0.297)	Chicago O’Hare		Chicago O’Hare	
	Charlotte Douglas (1.575)				
	İstanbul Atatürk (0.028)				
	Jakarta (0.344)				
Paris CDG	New York (0.196)	Paris CDG	New York (0.212)	Paris CDG	Hartsfield-Jackson (0.252)
			Charlotte Douglas (0.012)		Beijing (0.348)
	Jakarta (0.743)		Jakarta (0.320)		New York (0.051)
	Charlotte Douglas (0.209)		Hong Kong (0.307)		Hong Kong (0.349)
	Jakarta (0.743)		Hartsfield-Jackson (0.148)		

Dallas Fort Worth	Jakarta (1.034)	Dallas\ Fort Worth	Charlotte Douglas (0.389)	Dallas Fort Worth	Charlotte Douglas (0.041)
	Hong Kong (0.047)		Los Angeles (0.338)		Hartsfield-Jackson (0.281)
	Charlotte Douglas (1.210)		Hartsfield-Jackson (0.127)		Chicago O'Hare (0.481)
			Chicago O'Hare (0.145)		Los Angeles (0.196)
Amsterdam Schiphol	New York (1.133)	Amsterdam Schiphol	Hong Kong (0.128)	Amsterdam Schiphol	Hartsfield-Jackson (0.013)
	Hong Kong (0.117)		Chicago O'Hare (0.071)		Chicago O'Hare (0.092)
			New York (0.801)		New York (0.801)
					Hong Kong (0.147)
Singapur	Jakarta (0.524)	Singapur	Jakarta (0.495)	Singapur	Beijing (0.317)
	New York (0.293)		Hong Kong (0.291)		Hong Kong (0.291)
	Hong Kong (0.390)		New York (0.214)		Jakarta (0.050)
					New York (0.341)
Denver	Charlotte Douglas (0.990)	Denver	Jakarta (0.152)	Denver	Hartsfield-Jackson (0.097)

	Jakarta (1.019)		Charlotte Douglas (0.574)		Los Angeles (0.425)
			Los Angeles (0.274)		Charlotte Douglas (0.212)
					Los Angeles (0.425)
San Francisco	New York (0.331)	San Francisco	Charlotte Douglas (0.620)	San Francisco	Hartsfield-Jackson (0.060)
	Charlotte Douglas (0.407)		Jakarta (0.246)		New York (0.292)
	Jakarta (0.346)		New York (0.134)		Jakarta (0.294)
					Charlotte Douglas (0.355)
Bangkok Suvarnabhumi	Heathrow (0.129)	Bangkok Suvarnabhumi	Jakarta (0.838)	Bangkok Suvarnabhumi	Heathrow (0.129)
	Hong Kong (0.233)		Hong Kong (0.162)		Jakarta (0.638)
	Jakarta (0.638)				Hong Kong (0.233)

The number of times that efficient airports within the survey are referenced by inefficient airports are shown in Table 4:

Table 4: Efficient Airports and Reference Numbers

Efficient Airports	CCR Model	*Input-Oriented BCC Models*	*Output- Oriented BCC Models*
New York	4	4	4
Hong Kong	8	4	4
Jakarta	9	5	3
Los Angeles	------	2	2
Hartsfield-Jackson	------	2	5

İstanbul Atatürk	1	------	------
Beijing	------	------	2
Heathrow	------	------	1
Chicago O'Hare	------	2	3
Charlotte Douglas	6	4	3

5. Results and Recommendations

With today's increasing competition, it has become very important to obtain the most output by using the least possible number of inputs so that the scarce resources available in the world can be efficiently used. Since productivity and efficiency are recognized by all sectors, these sectors have acted together to investigate how efficiency and effectiveness should be measured. As a result of these investigations, many methods and analysis techniques have been developed. The data envelopment analysis (DEA) technique has been identified as the most widely used method for determining the relative efficiency of institutions and enterprises having similar decision-making units and for comparing them with other institutions and businesses. In this respect, it is important to consider the efficiency measurement that is necessary for the efficient and effective operation of airports with high investment costs, which play a key role in the aviation sector, and to take the data obtained as a result of this measurement into account.

In the CCR model based on the constant return assumption, only the scale activity can be measured, whereas in the BCC model based on the variable return assumption, the total efficiency as well as the technical efficiency can be measured. It was observed that 10 of the 20 airports were efficient and the other airports were below the efficiency value of the CCR model. According to the input-oriented BCC model, 14 of the 20 airports were found to be efficient and 6 airports were found inefficient. In the output-oriented BBC model, 13 airports were efficient and 7 airports were not efficient. Because the BCC model measures the technical efficiency, the efficiency values of the decision-making unit are higher than in the CCR model. If the decision-making unit is efficient according to the BCC model and not efficient according to the CCR model, it can be said that the relevant unit works locally efficiently and generally inefficiently. As the data envelopment analysis measures the relative efficiency, it can be said that efficient airports are not fully efficient, but they may be said to be efficient only in the airports involved in the analysis.

In the data envelopment analysis method, the airports that need to be referenced by the below-efficiency airports in order for them to reach the desired efficiency value can be determined. For example, Beijing Airport, which does not function efficiently, needs to refer to Jakarta Airport at 1,043, Hong Kong Airport at 0.162, and Heathrow Airport at 0.295 according to CCR model, and to reduce or increase the input and output values in accordance with these rates. This also applies to other airports that are not efficient.

Data envelopment analysis can also determine how many times the airports that are efficient are referenced by inefficient airports. Thus, it has been determined that Jakarta Airport has the highest reference for the CCR model and the input-oriented BCC model, and Hartsfield-Jackson Airport has the highest reference for the output-oriented BCC model. Therefore, Jakarta airport and Harstfield-Jackson airport can be taken as examples by other airports in terms of efficiency value.

As a result of the analysis, the following suggestions can be made to the authorities and managers of airports that are inefficient:

• Increasing the output variables such as the total number of flights before the existing capacity of the airports is increased,

• Increasing the number of output variables such as total number of flights, total load and total number of passengers by making agreements with airline operators using the airport,

• Making efforts to facilitate access to airports,

• Reducing fees charged from airline operators,

• Reducing the congestion at certain busy hours by giving discounts to the airline companies arriving at the airport at times when the airports are not used extensively,

• Reduction of waiting time at airports and improvement of flight conditions.

For such improvements, it is necessary for airline operators and ground handling companies to carry out joint operations and work collaboratively.

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