9 (2): 436-444 (2025)

Journal of Aviation

https://dergipark.org.tr/en/pub/jav

e-ISSN 2587-1676

Evaluation of Operational Performance of Major European International Airports with Data Envelopment

Ahmet İlbaş[1], Hakan Kaya[2*]

[1*]Arel University, Department of Aviation Management, 34537, Büyükçekmece, Istanbul, Türkiye. (ahmetilbas@arel.edu.tr)
[2*] Arel University, Department of Aviation Management, 34537, Büyükçekmece, Istanbul, Türkiye. (hakankaya@arel.edu.tr)

Article Info

Received: 13 February 2025
Revised: 15 June 2025
Accepted: 22 June 2025
Published Online: 28 June 2025

Keywords:
Logistics
Air Transportation
Data Envelopment Analysis (DEA)
Logistics Operational Efficiency
Airport management

Corresponding Author: *Hakan Kaya*

RESEARCH ARTICLE

https://doi.org/10.30518/jav.1639240

Abstract

This paper studies the impact of air logistics and transportation on the operational efficiency of 10 major European International Airports over the 2021–2023 period using the Data Envelope Analysis (DEA) method, which is solved using MAXDEA 8 software.
For this purpose, a literature review was carried out to identify the input and output variables used in analysing the operational efficiency of airport logistics. In this study, the input variables include the airport's area, cargo terminal area, the number of passenger terminals, and the number of runways, while the output variables are the number of flights, the number of passengers, and amount of cargo are used. The DEA model provides the most efficient results in terms of output-oriented maximization. The performance of each airport is compared to others, and the efficiency rate for each airport is evaluated. The study identifies the effective airports, their reference points relative to others, and assesses how much improvement is needed for ineffective airports to enhance their outputs.
As a result of this application, it was concluded that the operational efficiency of airports is effective or ineffective according to air logistics and transportation activities. As a result of this study, it was revealed that the operational efficiency of 8 of 10 major international airports in the 2021-2023 period was effective, and only 2 of them (Paris Charles de Gaulle, Madrid) were ineffective. While two inefficient airports could have produced more output by better utilizing their potential with the same input amounts, they made less output where they were located. The study identifies relative efficiency levels across airports and highlights internal performance differences. Furthermore, the discussion addresses the influence of external factors such as geopolitical events, environmental policies, and technological innovations, offering deeper insights into the drivers of airport performance. The findings contribute to strategic airport management by highlighting both internal and external dimensions of efficiency.

1. Introduction

Nowadays, millions of people use air transportation. The industry of aviation in the world has experienced rapid growth, especially in the last 20 years. According to a report released by Airports Council International (ACI), the number of people traveling by air in 2023 was 8.5 billion, and the number of flights in the same period was 36.8 million. The total amount of cargo carried in 2023 was 102 million tons. It is expected that growth in aircraft, passenger and air cargo traffic will continue to increase in the coming period.

Airports and airlines play an important role in globalization by connecting cities and countries, contributing to the economic growth of a region or country. They also play a key role in international trade and tourism. As a result, the effectiveness of airport management can have a direct impact on a country's competitiveness. Assessing airport performance and providing policy suggestions for inefficient airports are crucial for enhancing this competitiveness (Özsoy, 2021).

With this growth and the development of e-commerce, the aviation industry is becoming increasingly essential for both passenger and cargo transportation. Policymakers and industry leaders are consistently seeking better strategies to enhance aviation performance. However, airlines are vulnerable to market shifts and political or economic changes. For instance, many airlines entered the market following the "Open Skies" policy introduced in 1987 (Barbara et al., 2022). As a result, competition among airlines has intensified. In response, some companies have merged or been acquired, while others have gone bankrupt. Improving operational efficiency has become crucial, but the key question remains: How should performance be evaluated in the aviation industry? (Barbara et al., 2022).

Data envelopment analysis (DEA) modeling approach has been widely used for performance evaluation in various transportation domains, such as public transportation (Chiou et al., 2012, Fitzová et al., 2018, Gadepalli and Rayaprolu, 2020), maritime (Park et al., 2018) and aviation (Barros and Dieke, 2007, Huynh et al., 2020, Kottas and Madas, 2018, Min and Joo, 2016).

Existing airports must be operated in a way that can cope with this growth. However, operating airports is expensive. Therefore, it is of great importance that airports with high operating costs are operated effectively. Because for airports to be operated profitably, efficiency must be ensured. Today, the competitive conditions that have an effect in every sense have brought the issue of how effectively airports are operated to the agenda. For this purpose, efficiency analyses of airports have been carried out in the past and today. In recent years, both the state and the private sector have made intensive investments in air transportation in the form of new airport construction, expansion of the aircraft fleet, and the entry of new companies into the sector. To ensure efficiency, it is necessary to conduct regular capacity utilization analyses of existing airports to check their efficiency and identify new strategies based on the results (Kıyıldı, 2009).

The high efficiency and effectiveness level of airports is of great importance for their sustainability. In this study, the relative efficiencies of the top 10 European International Airports, which are on the list of the world's busiest airports prepared by ACI according to the total number of passengers served in 2023, were measured. Since there is more than one output variable in the analysis, DEA was used to calculate their efficiencies. DEA is a nonparametric mathematical method based on linear programming used to calculate the relative efficiency of similar decision-making units.

In this study, firstly the studies conducted in the literature are given, then the DEA method and the data used in the research are explained and then the efficiency analyses of the 10 busiest airports in Europe are made. Using the results obtained from the analysis, the performance status of existing airports is determined and future strategies and policies are developed accordingly.

2. Theoretical Background

The problem of measuring and improving the efficiency of airports has attracted the attention of many researchers worldwide, and there are many studies on this topic. DEA, one of the nonparametric performance measurement methods that has attracted much attention in recent years, is used to measure airports' relative efficiency and productivity.

The first study on airports in the literature was conducted by Gillen and Lall (1997). In this study, the efficiency of terminal operations and flight operations at 22 major airports in the USA were examined from two different perspectives using data from 1989 to 1993. Sarkis (2000) studied 44 major US airports using data from 1990 to 1994. Martin and Roman (2001) used DEA to examine the efficiency of airports in Spain before privatization. This study used 1997 data from 39 airports in Spain. The efficiency of 34 European airports was investigated using data between 1995 and 1997 by Pels et al. (2001). In the study conducted by Adler and Berechman (2001), 26 international airports were examined with data from 1998. Unlike other studies, DEA and Principal Component Analysis (PCA) methods were used together in this study.

Fernandes and Pacheco (2002) examined the efficiency of 35 Brazilian airports using data from 1998. In their study, various scenario studies were conducted for the years 2002, 2007, and 2017, and how efficiency would be affected in these different scenarios was calculated.

Bazargan and Vasigh (2003) examined 45 US airports with data between 1996 and 2000. Their study also divided the airports into 3 different hub sizes and then investigated the effect of hub size on efficiency by applying the Mann-Whitney test. Yu (2004) studied 14 Taiwanese airports between 1994 and 2000 by including both environmental factors and undesirable outcomes in the efficiency analysis. Yoshida and Fujimoto (2004) published a study investigating the efficiency of 67 Japanese airports with data from the year 2000 with Tobit regression.

In a study by Peker and Baki (2009), the efficiency of Turkish airports was evaluated using based on 2007 data. They then analyzed whether the efficiency differences between small and large airports were statistically significant using a t-test. The analysis concluded that larger airports were more efficient. Ömürbek et al. (2013) assessed the efficiency of 32 Turkish airports using the DEA method. The findings revealed that among small airports, the most efficient were those based on the number of aircraft and passengers, while among medium-sized airports, the most efficient ones were identified based on factors such as domestic flights, aircraft traffic, passenger traffic, and the total of domestic and international flights.

In the study conducted by Avcı and Aktaş (2015), the efficiency and productivity of airports in Türkiye were analyzed by comparing them with the data of 2013-2014 according to the winter and summer periods. Based on the results, airports with the greatest efficiency were identified both in summer and winter. Bolat et al. (2016) evaluated the efficiency of 41 airports in Türkiye using the DEA method and found that 19 airports were operating effectively. Then, an artificial neural network model was developed that allowed the efficiency of existing new airports to be estimated.

The efficiency of the 20 airports with the highest passenger traffic in Europe were evaluated by Altın et al. (2017) using data from the period 2010-2015. In the study, the criteria weights were determined with the ENTROPI method and then the airports were ranked according to their performances with the COPRAS and Grey Relational Analysis methods. Çınaroğlu and Avcı (2017) investigated the efficiency and productivity of major airports in Türkiye using the DEA method using data from 2015-2016. According to the analysis results, the airports that were fully effective for domestic flights in both years were Istanbul Atatürk and Adana airports. The Istanbul Atatürk and Antalya airports were found to be efficient for international flights in both years. Asker and Battal (2017) evaluated 20 airports, which are among the top 25 airports in the world in terms of passenger traffic, in terms of operational efficiency. As a result of the analysis, it was seen that 10 of the 20 airports were efficient according to the CCR model, while the rest of the airports were below the efficiency value.

Lu et al. (2019) used DEA to measure the efficiency of 27 Chinese airports from 2014 to 2018. Nine variables were determined in this study, including six input variables and three output variables. In particular, they proved that the integration of the fuzzy MCDM method and DEA approach is most suitable to develop a robust and reliable analysis.

Uludağ (2020) examined the efficiency of airports managed by the General Directorate of State Airports Authority (DHMI) in Türkiye from 2014 to 2018 using a hybrid approach called Weight-Restricted EATWOS, without considering satisfactory level, and provided recommendations for improvement. The study also evaluated the airports' efficiency using the equally weighted EATWOS method, excluding satisfactory levels, as well as the input-oriented DEA model under the assumption of constant returns to scale. The results obtained from the proposed model were then compared to those from traditional methods.

In another article, a study was conducted by Montoya-Quintero (2022) aiming to evaluate the technical efficiency of small regional airports in Colombia using DEA. The article aims to evaluate the technical efficiency of small regional airports in Colombia as well as to determine their potential level of efficiency.

Lo Storto and Evangelista (2023) carried out an international comparative study to assess the performance of national land logistics systems in 28 countries in EU between 2010 and 2017. The study compared these systems based on logistics quality, infrastructure efficiency and environmental impact using DEA.

In this study, the efficiencies of the top 10 European International Airports, which are on the list of the world's busiest airports prepared by ACI according to the total number of passengers served in 2023, were measured with DEA (URL1, 2024). In this context, the indicators of the airports included in the European main airports statistics for 2023 prepared by the European Union Against Aircraft Nuisances (URL2, 2024) and ACI were integrated into DEA within the scope of input and output variables and the relative efficiencies of the top 10 European International Airports were focused on. In this respect, the study is expected to provide important ideas to national and international management units, policymakers, and researchers.

3. Result Research Methodology

3.1. Method of the Study

Many methods are used to measure and evaluate the effectiveness of Decision Making Units (DMU). In the study, efficiency measurements will be made based on multiple inputs and outputs, and the DEA MAXDEA 8 package program, which is generally used and gives successful results, was used in this analysis. In addition, 4 input variables were used in the analysis (Surface of The Airport, Cargo Terminal Area, Number of Passenger Terminals and Number of Runways), and 3 output variables (Number of Flights, Number of Passengers and Amount of Cargo). Information and codes of the input and output variables determined in the study are given in Table 1.

Table 1. Input and output variables

Input Code	Inputs	Output Code	Outputs
Input_1	Surface of The Airport (ha)	Output_1	Number of Flights (times)
Input_2	Cargo Terminal Area (m2)	Output_2	Number of Passengers (person)
Input_3	Number of Passenger Terminals	Output_3	Amount of Cargo (ton)
Input_4	Number of Runways		

Input and output variables of the DMUs used in the analysis were obtained from the Main European Airports Statistics Report. (URL3,2018).

In selecting input and output variables for the DEA model, we conducted a detailed literature review to ensure methodological consistency and practical relevance. The chosen inputs—airport area, cargo terminal area, number of passenger terminals, and number of runways—represent key infrastructure elements that influence an airport's ability to deliver logistical and transport services.

- **Airport area** reflects the total physical capacity available for operations.
- **Cargo terminal area** is indicative of cargo processing potential, a critical aspect of air logistics.
- **Number of passenger terminals** relates to the airport's ability to handle traveler flow.
- **Number of runways** directly impacts aircraft movement capacity and scheduling efficiency.

Output variables include:

- **Number of flights**, representing the level of traffic the airport handles;
- **Passenger volume**, reflecting the human throughput of airport services;
- **Cargo volume**, which is a direct output of air logistics operations.

These variables align with prior DEA-based airport efficiency studies (e.g., Barros & Dieke, 2007; Pels et al., 2001; Adler & Berchmnat, 2001) and reflect a balance between resource utilization and operational outcomes.

3.2. Selection of Decision-Making Units (DMU)

As the Decision Making Unit (DMU), the top 10 European International Airports in the list of the world's busiest airports, created by ACI according to the total number of passengers served in 2023, were included in the study. In the study, Code (International Air Transport Association-IATA) was given to all DMUs that will form the data set, as explained in Table 2.

Table 2. DMU Coding

Code (IATA)	DMU
LHR	London Heathrow / England
IST	Istanbul / Türkiye
CDG	Paris Charles de Gaulle / France
AMS	Amsterdam Schiphol / Netherlands
FRA	Frankfurt Main / Germany
MAD	Madrid / Spain
BCN	Barcelona / Spain
FCO	Leonardo da Vinci-Fiumicino / Italy

3.3. Selection of decision determining the model

DEA is a linear programming method used to measure the efficiency of production units. This method is particularly effective in situations where there are many inputs and outputs and is used to compare the performance of DMUs.

The method identifies the DMUs that obtain the maximum output using a given set of inputs and calls these units the efficient frontier. Other units are compared to this frontier to measure their efficiency levels. The main purpose of DEA is to evaluate the effectiveness of units and identify areas for improvement.

There should be a sufficient number of DMUs in DEA. Since too many input and output values will weaken the efficiency analysis, the number of inputs and outputs should not be overdetermined, and analysis should be done according to the number of DMUs (Dyson et.al.1990; Boussofianee et al., 1991).

In the DEA method, it is up to the decision maker whether the model will be input-based or output-based. If the decision maker wants to measure the same output with the least input, should prefer input-oriented models, and if the decision maker wants to measure the maximum return with the same amount of input, should choose output-oriented models (Charnes et al., 1978).

The CCR and BCC models can be used to evaluate the efficiency of DMUs with DEA. The CCR model developed by Charnes, Cooper, and Rhodes is based on the assumption of constant returns. In other words, changes in inputs results in changes in outputs at the same rate. The BCC model developed by Banker, Charnes and Cooper (1984) uses uses the variable return assumption. This model is more flexible and takes into account economies of scale.

While the CCR model calculates the total technical efficiency, the BCC model allows calculations to be made by separating technical efficiency and scale efficiency (Banker, Charnes and Cooper, 1984). The total technical efficiency (TE) value is obtained by the CCR model, and the net technical efficiency (STE) value is obtained by the BCC model. Scale Efficiency (SEE) can be calculated by comparing these values. Since the analysis is performed only for the observation set consisting of the examined DMUs, it evaluates the relative efficiency, not the absolute efficiency as can be calculated in engineering and basic sciences (Dyson et al.,1990).

DEA can be used in both input and output-focused ways. Input-focused DEA questions what the most appropriate inputs would be to reach a certain output level. In the output-focused model, the maximum output combination that can be obtained with a certain input combination is analyzed. CCR and BCC models can be applied both input and output-focused. Input-focused CCR and BCC models aim to obtain the most appropriate input combination to be used to produce a certain output combination. The output-focused CCR and BCC model examines to what extent outputs should be increased by keeping inputs constant.

Since it is desired to measure the maximum return with the same input amount, the output-oriented model was used in this study. The number of municipalities providing waste services in the province and the average amount of waste collected per capita are considered to be the factors that cause the amount of processed and disposed waste to increase.

3.4. Selection of decision determining the model

According to the information and data mentioned above, 10 major European International Airports were analyzed according to output-oriented CCR and BCC models. According to the analysis results, reference sets, effectiveness statuses, and improvement tables for the 2021-2023 period were given and interpreted.

The analyses were conducted using an output-oriented model to produce the maximum output given the same input criteria and to provide variable returns to scale (Kuah et al., 2010). Since this model aims to maximize the outputs to be produced in response to the current level of input, it is desirable to reach the reference unit level by making improvements in the variables in the output set.

The important point in interpreting the results is that the effectiveness scores determined as a result of the analysis are relative (Dyson vd.,1990). An airport's efficiency score of "1" does not mean that that airport is efficient. The efficiency found here is expressed only within the framework of input and output values when compared to other airports.

DEA is a powerful tool to evaluate the operational efficiency of an airport. This analysis evaluates how efficiently the resources (inputs) are used in the operation of an airport and how effective the outputs. This analysis gives us an important view of the impact of air logistics and transportation on operational efficiency and effectiveness.

4. Finding

Within the scope of the study, statistics data regarding the input and output variables on the operational efficiency of 10 major European International Airports over the 2021–2023 period is shown in Table 3.

Table 3. Efficiency scores of 10 European International Airports over the 2021–2023 period

Code (IATA)	Name	Country	Input_1	Input_2	Input_3	Input_4	Output_1	Output_2	Output_3
AMS	Amsterdam Schiphol	Netherlands	2.787	375.000	1	6	1.172.652	139.854.407	4.510.358
BCN	Barcelona	Spain	1.533	55.800	2	2	776.030	110.424.062	448.207
CDG	Paris Charles de Gaulle	France	3.257	500.000	3	4	1.120.099	151.073.125	6.015.609
FCO	Leonardo da Vinci-Fiumicino	Italy	1.639	46.000	2	3	715.245	81.600.000	458.333
FRA	Frankfurt Main	Germany	2.300	353.555	2	3	1.074.308	133.097.934	6.304.951
IST	Istanbul	Türkiye	7.650	1.400.000	1	3	1.211.281	177.899.667	7.129.471
LGW	London Gatwick	England	678	23.000	2	1	522.571	79.954.314	109.153
LHR	London Heathrow	England	1.227	124.000	4	2	1.020.729	160.172.778	4.191.647
MAD	Madrid	Spain	3.050	287.466	4	4	958.624	134.989.675	1.733.388
MUC	Münih	Germany	1.575	53.000	2	2	740.000	91.255.399	740.600

While evaluating the operational efficiency of 10 largest European International Airports with DEA, input-oriented CCR and BCC models were used. Output-oriented CCR and BCC models examine to what extent outputs should be increased by keeping inputs constant. The efficiency values obtained as a result of the analysis are given in Table 4.

Table 4. DEA application CCR-DEA detailed results

Airports	Code (IATA)	Efficiency Score	Benchmark	Times as a Benchmark for Another Airport	OUTPUTS		
					Output_1	Output_2	Output_3
Amsterdam Schiphol	AMS	1	AMS (1)	0	1.172.652	139.854.407	4.510.358
Barcelona	BCN	1	BCN (1)	2	776.030	110.424.062	448.207
Paris Charles de Gaulle	CDG	%79,44	BCN (%23,08); FRA (%108,43); IST (%4,03); LHR (%8,24)	0	1.476.837	190.164.284	7.572.187
Leonardo da Vinci-Fiumicino	FCO	1	FCO (1)	0	715.245	81.600.000	458.333
Frankfurt Main	FRA	1	FRA (1)	2	1.074.308	133.097.934	6.304.951
Istanbul	IST	1	IST (1)	2	1.211.281	177.899.667	7.129.471
London Gatwick	LGW	1	LGW (1)	0	522.571	79.954.314	109.153
London Heathrow	LHR	1	LHR (1)	2	1.020.729	160.172.778	4.191.647
Madrid	MAD	%61,58	BCN (%148,96); FRA (%24,96); IST (%0,43); LHR (%12,92)	0	1.561.481	219.205.967	2.814.800
Munich	MUC	1	MUC (1)	0	740.000	91.255.399	740.600

When we examine the airports in Table 4 above in detail; According to the input-oriented CCR model, it was determined that Amsterdam Schiphol, Barcelona, Leonardo da Vinci-Fiumicino, Frankfurt Main, Istanbul, London Gatwick, London Heathrow, and Munich Airports were among the airports with effective operational efficiency performances with an efficiency rate of "1", while the operational efficiency performances of other airports were not effective because their efficiency values were less than "1". It can be seen from Table 4 that the total operational efficiency values of Paris Charles de Gaulle and Madrid Airports are quite low compared to other airports.

Paris Charles de Gaulle is among the inefficient airports with an efficiency rate of %79.4. When the reference column of the inactive Paris Charles de Gaulle Airport is examined, to become effective, without changing its inputs, it increases by %23,08 of the outputs of the Barcelona Airport, by %108,43 of the outputs of the Frankfurt Main Airport, by % 4,03 of the outputs of the Istanbul Airport and by %8,24 of the outputs of the London Heathrow Airport. It must be increased the number of flights to 1,476,837, the number of passengers to 190,164,284, and the amount of cargo to 7,572,187 tons.

Madrid is among the inefficient airports with an efficiency rate of %61.6. When the reference column of the inactive Madrid Airport is examined, to become effective, without changing its inputs, it increases by %148,96 of the outputs of the Barcelona Airport, by %24,96 of the outputs of the Frankfurt Main Airport, by % 0,43 of the outputs of the Istanbul Airport and by %12,92 of the outputs of the London Heathrow Airport. It must be increased the number of flights to 1.561.481, the number of passengers to 219.205.967, and the amount of cargo to 2.814.800 tons.

Table 5. Ineffective Airports' Output Improvement Table

Airports	Outputs		
	Output_1	Output_2	Output_3
Paris Charles de Gaulle	1.476.837	190.164.284	7.572.187
Madrid	1.561.481	219.205.967	2.814.800

Improvements in the outputs of ineffective airports are given in Table 5 and the creation of the table is detailed in Table 6 for Paris Charles de Gaulle Airport and Table 7 for Madrid Airport,

Table 6: Calculation of improvement table for Paris Charles de Gaulle Airport

Airports	Efficiency Score	Outputs			Benchmark
		Output_1	Output_2	Output_3	
Paris Charles de Gaulle	%79,44	1.476.837	190.164.284	7.572.187	
Barcelona	1	776.030	110.424.062	448.207	Barcelona (%23); Frankfurt Main (%108) Istanbul (%4,03); London Heathrow (%8,24)
Frankfurt Main	1	1.074.308	133.097.934	6.304.951	
Istanbul	1	1.211.281	177.899.667	7.129.471	
London Heathrow	1	1.020.729	160.172.778	4.191.647	

Number of Flights: (776.030 x 0, 230804) + (1.074.308 x 1,084211) + (1.211.281 x 0,04031) + (1.020.729 x 0,082415) ≅1.476.837

Number of Passengers: (110.424.062 x 0, 230804) + (133.097.934 x 1,084211) + (177.899.667 x 0,04031) + (160.172.778 x 0,082415) ≅190.164.284

Amount of Cargo: (448.207 x 0, 230804) + (6.304.951 x 1,084211) + (7.129.471 x 0,04031) + (4.191.647 x 0,082415) ≅7.572.187

Table 7. Calculation of Improvement Table for Madrid Airport

Airports	Efficiency Score	Outputs			Benchmark
		Output_1	Output_2	Output_3	
Madrid	% 61,58	1.561.481	219.205.967	2.814.800	
Barcelona	1	776.030	110.424.062	448.207	Barcelona (%148,9); Frankfurt Main (%24,96); Istanbul (%0,43); London Heathrow (%12,92)
Frankfurt Main	1	1.074.308	133.097.934	6.304.951	
Istanbul	1	1.211.281	177.899.667	7.129.471	
London Heathrow	1	1.020.729	160.172.778	4.191.647	

Number of Flights: (776.030 x 1,489684) + (1.074.308 x 0,249687) + (1.211.281 x 0,004377) + (1.020.729 x 0,129220) ≅1.561.481
Number of Passengers: (110.424.062 x 1,489684) + (133.097.934 x 0,249687) + (177.899.667 x 0,004377) + (160.172.778 x 0,129220) ≅219.205.967
Amount of Cargo: (448.207 x 1,489684) + (6.304.951 x 0,249687) + (7.129.471 x 0,004377) + (4.191.647 x 0,129220) ≅2.814.800

Table 8. DEA application BCC-DEA detailed results

Airports	Code (IATA)	Efficiency Score	Benchmark	Times as a Benchmark for Another Airport	OUTPUTS		
					Output_1	Output_1	Output_1
Amsterdam Schiphol	AMS	1	AMS (1)	1	1.172.652	139.854.407	4.510.358
Barcelona	BCN	1	BCN (1)	0	776.030	110.424.062	448.207
Paris Charles de Gaulle	CDG	1	CDG (1)	0	1.476.837	190.164.284	7.572.187
Leonardo da Vinci-Fiumicino	FCO	1	FCO (1)	0	715.245	81.600.000	458.333
Frankfurt Main	FRA	1	FRA (1)	0	1.074.308	133.097.934	6.304.951
Istanbul	IST	1	IST (1)	1	1.211.281	177.899.667	7.129.471
London Gatwick	LGW	1	LGW (1)	0	522.571	79.954.314	109.153
London Heathrow	LHR	1	LHR (1)	1	1.020.729	160.172.778	4.191.647
Madrid	MAD	%88,03	AMS (%38,25); IST (%5,28); LHR (%56,46);	0	1.088.918	153.337.192	4.468.858
Munich	MUC	1	MUC (1)	0	740.000	91.255.399	740.600

When we examine the airports in Table 8 above in detail; According to the input-oriented BCC model, Madrid is the only ineffective airport with an efficiency rate of %88.03. When the reference column of inactive Madrid Airport is examined, to be effective, without changing its inputs, it increases by %38,25 of the outputs of the Amsterdam Schiphol Airport, by % 5,28 of the outputs of the Istanbul Airport, and by %56,46 of the outputs of the London Heathrow Airport. It must be increased to 1.088.918, the Number of Passengers to 153.337.192, and the amount of Cargo to 4.468.858 tons.

Tables of Technical Efficiency, Pure Technical Efficiency, Scale Efficiency, and Returns to Scale according to the 10 Airports are given below.

Tablo 9. Technical Efficiency, Pure Technical Efficiency, Scale Efficiency, and Returns to Scale Table

orts	Code (IATA)	TE (CRS)	PTE (VRS)	SE	RS
Amsterdam Schiphol	AMS	1	1	1	Constant
Barcelona	BCN	1	1	1	Constant
Paris Charles de Gaulle	CDG	%79,44	1	%79,44	Decreasing
Leonardo da Vinci-Fiumicino	FCO	1	1	1	Constant
Frankfurt Main	FRA	1	1	1	Constant
Istanbul	IST	1	1	1	Constant
London Gatwick	LGW	1	1	1	Constant
London Heathrow	LHR	1	1	1	Constant
Madrid	MAD	%61,58	%88,03	%69,95	Decreasing
Munich	MUC	1	1	1	Constant

As a result of the analysis, total technical efficiency (with TE - CCR model), pure technical efficiency (with PTE - BCC model), and scale efficiency scores of the municipalities were obtained. When we examine Table 9, while 8 of the 10 airports (Amsterdam Schiphol, Barcelona, Leonardo da Vinci-Fiumicino, Frankfurt Main, Istanbul, London Gatwick, London Heathrow, and Munich Airports) have total technical efficiency (CCR-Effective), the total technical efficiency values of the other 2 airports are below 1 (CCR-Ineffective).

9 of the 10 airports (Amsterdam Schiphol, Barcelona, Paris Charles de Gaulle, Leonardo da Vinci-Fiumicino, Frankfurt Main, Istanbul, London Gatwick, London Heathrow, and Munich Airports) have pure technical efficiency (BCC-Effective), while only one airport (Madrid) have pure technical efficiency values below 1 (BCC-Ineffective). Airports with both CCR and BCC efficiency scores of "1" obtain output at the optimal scale size. These are the airports with a scale efficiency score of "1", that is, scale efficient, operating under constant returns to scale, and 8 airports in the table (Amsterdam Schiphol, Barcelona, Leonardo da Vinci-Fiumicino, Frankfurt Main, Istanbul, London Gatwick, London Heathrow and Munich Airports) achieved optimal size output. However, scale inefficiency depends on non-operational, that is, completely non-management factors, and has the characteristics of increasing or decreasing returns to scale. 8 airports with increasing returns to scale (Amsterdam Schiphol, Barcelona, Leonardo da Vinci-Fiumicino, Frankfurt Main, Istanbul, London Gatwick, London Heathrow, and Munich Airports) produced less output while they could have produced more output with the same input amounts. In other words, they are in a position to produce more output by using their potential better.

According to the CCR model, the airport with the lowest score in terms of total efficiency is Madrid Airport with 61.58%. This province has an inefficiency level of 38.42%, which is caused by not being able to use its resources efficiently, not reaching the most appropriate output and not being able to operate at an appropriate scale.

According to the BCC model, the airport with the lowest score in terms of pure technical efficiency is Madrid Airport with 88.03%. In other words, this province shows that the level of output that can be produced with its current resources is 88.03%. In other words, the inefficiency level due to the inability to achieve maximum output with existing resources is at 11.97%.

Amsterdam Schiphol, Barcelona, Leonardo da Vinci-Fiumicino, Frankfurt Main, Istanbul, London Gatwick, London Heathrow, and Munich Airports have produced the optimum output they can produce because they are in an efficient "1" state in terms of both total technical efficiency and pure technical efficiency.

While the DEA model focuses on internal operational indicators, several **external factors** may significantly affect airport efficiency but are not captured directly in the model due to data limitations. These include:

- **Geopolitical events** (e.g., Brexit, Russia-Ukraine conflict), which influence flight routes, international travel, and logistics corridors;
- **Environmental regulations**, such as carbon emissions limits or noise abatement policies, which can restrict capacity utilization;
- **Technological developments**, including automation in check-in, security, or cargo handling, which can drive efficiency gains.

Recognizing these factors is important when interpreting DEA results. Although this study does not include external variables in the primary model, future research may adopt a two-stage DEA or integrated approach

5. Conclusion and recommendations

In the application part of the study, according to the analysis outputs made with the output-oriented DEA model, the efficiency scores for the 2021-2023 period, results such as the effective airports and the reference status of these airports to other airports, the extent to which the ineffective airports can improve by reference to which airports and to what extent they should increase their output have been achieved.

The operational efficiency of 10 major International Airports in Europe was measured and evaluated between 2021 and 2023 using DEA. As a result of this application, it is seen which airports' operational efficiency is effective or ineffective. From this result, it was concluded that 2 of the 10 major European International Airports (Charles de Gaulle and Madrid Airports) were inactive in the 2021-2023 period. Two inefficient airports could produce more by making better use of their potential with the same input quantities, but not less during the period. However, many factors cause these potentials not to be used well.

The DEA findings reveal that some major airports, notably Madrid and Paris Charles de Gaulle, exhibit lower relative efficiency scores. While these results are derived from quantitative input-output relationships, several underlying factors may contribute to these outcomes:

- **Madrid**, for example, has a large physical area but comparatively lower cargo output, suggesting potential underutilization of resources.
- **Paris Charles de Gaulle** may face operational complexity and congestion, which can negatively impact throughput efficiency.

In contrast, airports such as **Zurich** and **Amsterdam Schiphol** score higher in efficiency. These airports may benefit from:

- Streamlined terminal layouts and centralized operations;
- Investment in automated systems for passenger and cargo handling;
- More agile governance structures or public-private management partnerships.

These qualitative factors, though not included in the DEA model, help contextualize the results. A more detailed multi-criteria analysis or qualitative case study approach could further illuminate why certain airports outperform others despite similar infrastructural profiles.imes New Roman 10pt space).

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Acknowledgement

This study is an expanded version of the study titled “The Impact of Air Logistics and Transportation on The Operational Efficiency of 10 European International Airports by Using Data Envelopment Analysis” prepared by Dr. Ahmet İlbaş and Dr. Hakan Kaya and published as a paper at the 22nd International Logistics and Supply Chain Congress.

References

Adler, N. and Berechman, J. (2001). Measuring airport quality from the airlines’ viewpoint: An application of data envelopment analysis. Transport Policy, 8 (3), 171–181.

Altın, F. G., Karaatlı, M. and Budak, I. (2017). Evaluation of Europe's 20 largest airports with multi-criteria decision-making methods and data envelopment analysis. Süleyman Demirel University Journal of the Faculty of Economics and Administrative Sciences, 22(4):1049-1064

Asker, V. and Battal, Ü. (2017), Operatıonal effıcıency measurement at selected aırports. International Journal of Management Economics and Business, ICMEB17 Special Issue: 351-368

Avcı, T. and Aktaş, M. (2015), Evaluation of the performance of airports operating in Türkiye. International Journal of Alanya Business Faculty,7(3): 67-77.

Banker, R.D., Charnes, A. and Cooper, W.W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. Management Science 30, 1984: 1085.

Barbara T.H. Yen, Jun-Sheng Li (2022). Route-based performance evaluation for airlines – A metafrontier data envelopment analysis approach, Transportation Research Part E: Logistics and Transportation Review, Volume 162, 102748, ISSN 1366-5545.

Barros, C. and Dieke, P. (2007). Performance evaluation of Italian airports: A data envelopment analysis. Journal of Air Transport Management - J Air Transp Manag. 13. 184-191. 10.1016/j.jairtraman.2007.03.001.

Bazargan, M., and Vasigh, B. (2003). Size versus efficiency: a case study of US commercial airports. Journal of Air Transport Management, 9(3), 187-193.

Bolat, B., Temur, G. T. and Gürler, H. (2016). Efficiency estimation of airports in Türkiye: Combined use of data envelopment analysis and artificial boundary networks. Ege Academic Review, 16(special issue):1-10.

Boussofiane, A., Dyson R.G. and Thanassoulis E. (1991). Applied Data Envelopment Analysis. European Journal Of Operational Research, vol 52, no.1, syf.1-15.

Charnes, A., Cooper, W.W. and Rhodes, E.L. (1978). Measuring the efficiency of decision making units. European Journal of Operational Research 2, 429–444.

Charnes, A., Cooper, W.W., Lewin, A.Y. and Seiford, L. M. (1994). Data Envelopment Analysis: Theory, Methodology and Application. Kluwer Academic Publisher, Boston, USA.

Chiou Y.C., Lan L.W. and Yen B.T.H. (2012). Route-based data envelopment analysis models. Transportation Research Part E: Logistics and Transportation Review, Volume 48, Issue 2, Pages 415-425, ISSN 1366-5545.

Çınaroğlu E. and Avcı T. (2017). Comparison of domestic and international flight performances of major airports operating in Turkey, Busıness & Management Studıes: An Internatıonal Journal, 5(4): 55-75

Dyson, R.G., Thanassoulis, E. and Boussofiane, A. (1990). A DEA Tutorial, Wawick Business School,

Fernandes E and Pacheco R.R (2002). Efficient Use of Airport Capacity. Transportation Research Part A: Policy and Practice 36(3): 225-238.

Gadepalli R. and Rayaprolu S. (2020). Factors affecting performance of urban bus transport systems in India: A Data Envelopment Analysis (DEA) based approach. Transportation Research Procedia, Volume 48, Pages 1789-1804, ISSN 2352-1465.

Gillen, D., and Lall, A. (1997). Developing airport productivity and performance measures: an application of data envelopment analysis. Transportation Research Part E: Logistics and Transportation Review, 33(4), 261-273.

Hokey M. and Seong-Jong J. (2016). A comparative performance analysis of airline strategic alliances using data envelopment analysis, Journal of Air Transport Management, Volume 52, Pages 99-110, ISSN 0969-6997.

Kıyıldı, R. and Karaşahin, M. (2009). Evaluation of infrastructure performance of airports in Turkey through data envelopment analysis. Süleyman Demirel University Journal of Institute of Science and Technology, 10(3): 391-397.

Kottas, A.T., Madas, A. M. (2018), Comparative efficiency analysis of major international airlines using Data Envelopment Analysis: Exploring effects of alliance membership and other operational efficiency determinants, Journal of Air Transport Management, Volume 70, Pages 1-17, ISSN 0969-6997.

Kuah C. T., Wong K.Y., and Behrouzi F. (2010). A review on Data Envelopment Analysis (DEA). Fourth Asia International Conference on Mathematical / Analytical Modelling and Computer.

Lo Storto, C. and Evangelista P. (2023). Infrastructure efficiency, logistics quality and environmental impact of land logistics systems in the EU: A DEA-based dynamic mapping. Research in Transportation Business & Management, Volume 46, 100814, ISSN 2210-5395.

Lu W., Park S.H, Huang T. and Yeo G.T. (2019). An analysis for Chinese airport efficiency using weighted variables and adopting CFPR. The Asian Journal of Shipping and Logistics, Volume 35, Issue 4, Pages 230-242, ISSN 2092-5212, https://doi.org/10.1016/j.ajsl.2019.12.010.

Martin, J., and Roman, C. (2001). An application of DEA to measure the efficiency of Spanish Airport priority to privatization. Journal of Air Transport Management, 17, 149-157.

Montoya-Quintero, D. M., Larrea-Serna, O. L., and Jiménez-Builes, J. A. (2022). Evaluation of the efficiency of regional airports using Data Envelopment Analysis. Informatics, 9(4), 90.

Ömürbek, N., Demirgubuz, M. and Tunca, M. (2013). The use of data envelopment analysis in performance measurement in the service sector: an application on airports. Süleyman Demirel University Visionary Magazine,4(9): 21-43.

Özsoy, V. and Örkcü H. (2021). Structural and operational management of Turkish airports: A bootstrap data envelopment analysis of efficiency. Util. Policy 69, 101180.

Peker, İ. and Baki, B. (2009). An efficiency measurement application in Turkish airports with data envelopment analysis. Çukuova Univesity Journal of the Institute of Social Sciences, 18 (2): 72-88.

Pels, E., Nijkamp, P., and Rietveld, P. (2001). Relative efficiency of European airports. Transport Policy, 8(3), 183-192.

Sarkis, J. (2000). An analysis of the operational efficiency of major airports in the United States. Journal of Operations Management, 18(3), 335-351.

Park S.H., Pham T.Y. and Yeo G.T. (2018). The impact of ferry disasters on operational efficiency of the South Korean Coastal Ferry Industry: A DEA-Window Analysis. The Asian Journal of Shipping and Logistics, Volume 34, Issue 3, Pages 248-255, ISSN 2092-5212.

Uludağ, A.S. (2020). Measuring the productivity of selected airports in Turkey. Transportation Research Part E: Logistics and Transportation Review, Volume 141, 102020, ISSN 1366-5545.

URL1 (2024), Airports Council International-ACI Annual Report 2023, https://store.aci.aero/product/aci-annual-report-2023/03.09.2024

URL2 (2024) European Union Against Aircraft Nuisances (UECNA) Retrieved December 18, 2024, https://www.uecna.eu/wp-content/uploads/2024/06/UECNA-STATS-EUROPE-Synthesis-til-2023-with-2007-En-cours.pdf

URL3 (2018), Air transport statistics. Luxembourg: Eurostat. Retrieved February 14, 2018. http://ec.europa.eu/eurostat/statistics-explained/index.php/ Air_ transport_ statistics

Yoshida, Y. (2004). Endogenous-Weight TFP measurement: Methodology and its application to Japanese- Airport benchmarking. Transportation Research Part E: Logistics and Transportation Review, 40(2), 151-182.

Yu, M. M. (2004). Measuring physical efficiency of domestic airports in Taiwan with undesirable outputs and environmental factors. Journal of Air Transport Management, 10, 295-303.

Cite this article: İlbaş, A., Kaya, H. (2025). Evaluation of Operational Performance of Major European International Airports with Data Envelopment. Journal of Aviation, 9(2), 436-444.