Applied Soft Computing 119 (2022) 108620

Contents lists available at ScienceDirect

Applied Soft Computing

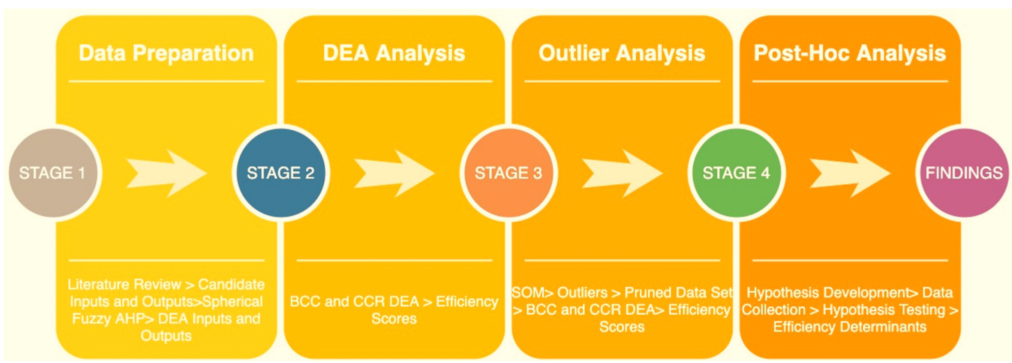
journal homepage: www.elsevier.com/locate/asoc

The evaluation of operational efficiencies of Turkish airports: An integrated spherical fuzzy AHP/DEA approach

Mustafa K. Yilmaz [a], Ali Osman Kusakci [a,*], Mine Aksoy [b], Umit Hacioglu [a]

[a] School of Business, Ibn Haldun University, Başak Mah. Ordu Cad. F-05 Blok No: 3 34480, Başakşehir, Istanbul, Turkey
[b] Yalova University, Faculty of Economics and Administrative Sciences, Yalova University, Merkez Yerleşkesi, Çınarcık Yolu Üzeri, 77200, Yalova, Turkey

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 9 September 2021
Received in revised form 26 January 2022
Accepted 11 February 2022
Available online 18 February 2022

Keywords:
Airport efficiency
SFS-AHP
DEA
Tobit regression
Turkish airports

ABSTRACT

The demand for air transport services has significantly increased around the globe, which has brought new investments in airports, which, in turn, requires in-depth efficiency analysis of these capital-intensive endeavors. This study examines the operational efficiencies of 46 Turkish civil airports from 2015 to 2018. We employ a novel hybrid methodology that combines Spherical Fuzzy Sets based Analytic Hierarchy Process (SFS-AHP) and Data Envelopment Analysis (DEA), which provides a solid basis for efficiency analysis. To this end, it can handle the hesitancy and uncertainty that the subjective evaluation process of input and output factors possess. Then, we use Self Organizing Maps (SOM), a machine learning method for clustering, to examine the effect of outlier airports on the efficiency scores. Finally, a posthoc analysis is conducted with Tobit regression model to assess the explanatory power of external factors on the efficiency scores, i.e., tourism potential, number of international flights, distance to the city center, population, public/private ownership, and age of airport. The findings show that 67.2% of the Turkish airports operate below the optimal efficiency level, and 93.5% of them should make considerable efforts to refine their operations by implementing managerial and structural changes to reduce input factors. The results also suggest that the airports located in high-density touristic areas achieve higher efficiency levels. Those relatively closer to the city center lead to more airport traffic, generating more revenues. Thus, both factors have a significant impact on efficiency scores. The study provides a novel efficiency analysis framework for airport operators and policy makers that helps them make informed decisions.

1. Introduction

The Air transport industry plays a vital role in connecting countries and contributes significantly to the economic growth of

* Corresponding author.
E-mail addresses: mustafa.yilmaz@ihu.edu.tr (M.K. Yilmaz), aliosman.kusakci@ihu.edu.tr (A.O. Kusakci), maksoy@yalova.edu.tr (M. Aksoy), umit.hacioglu@ihu.edu.tr (U. Hacioglu).

https://doi.org/10.1016/j.asoc.2022.108620
1568-4946/

nations, acting as a catalyst for international trade. The effective working mechanism of the industry is a kegüy factor for ensuring the safety of passengers and product transportation between airports across the globe. In this frame, airports should provide efficient operating services by qualified labor force at the international standards by offering high quality, safe, and human- and environment-sensitive infrastructure to the passengers, airlines, and other customers.

Since airports are complex entities, the authorities are expected to rapidly adapt to changing global conditions and manage costly operational activities to increase efficiency in machine park, human resources, slot rights, and energy use [1,2]. Under this challenging environment, countries follow different policies, i.e., renewing existing terminals, opening new terminals, or transferring terminal management to the private sector to maximize profitability and to offer the best quality services to customers. Another striking trend in the air transport industry is the increasing role of private operators in airport management. The private sector primarily considers the profitability of the airports, mostly focusing on their size and attractiveness in terms of high international scope rather than on social and demographical factors. Hence, these attributes underline the importance of efficiency measurement among airports, particularly for the public-owned ones, in pinpointing potential areas for improvement through new policies.

On the operational side, airports and air navigation services are operated by a central airport authority in many European countries, including Turkey [3]. Turkey has 53 civil airports countrywide. The Turkish General Directorate of State Airports (TGDSA), as a state-owned enterprise, regulates and controls the management of airports and the Turkish airspace in Turkey. TGDSA also handles public–private partnerships via build–operate–transfer (BOT) contracts.

Given its strategic nature, the efficiency of the airports is of paramount importance in Turkey, like in other countries. According to the World Airport Traffic Report, 2019, the global air passenger transport industry has recorded an average growth rate of 6.4 percent in 2018. Airports could handle 7.2 billion passengers and more than 122 million tons of air cargo, while Turkey has recorded 8.8 percent growth, carrying 210 million passengers and 1.4 million tons of air cargo [4]. Additionally, according to the United Nations World Tourism Organization 2019, Turkey is ranked sixth in the international tourist arrivals with 52 million tourists and USD 34.5 billion in revenues in 2019. Hence, it is vital to execute the right policies to increase airports' efficiency to keep this growth rate sustainable.

Several studies are held on airport efficiency covering operational, technical, scale dimensions and employing hybrid multicriteria decision-making techniques [5–12]. Among many, passenger boarding capacity, low-cost regional airline routes, airline traffic management, detection of the best alternative secondary runaway, maintenance planning, infrastructure management, uncertainty management, scale, optimization for airport gate assignment are some of the aspects used for measuring efficiency.

Additionally, several techniques measure the efficiency scores of airports in related literature. Data Envelopment Analysis (DEA) and related hybrid models are the most prominent ones. They measure the efficiency levels of airports by using different input- and output measures [1,13–16]. Furthermore, recent works employ a two-step procedure for measuring airport efficiency. In the first step, the DEA method is employed to evaluate the efficiency of each airport. In the second step, regression analysis is used to identify the aspects that influence airport efficiency [17,18]. Similarly, the performance of the Turkish airports can be associated with specific determinants, such as tourism potential, the population residing in the vicinity of the airports, which will be questioned in the present study as well.

However, an overview of the relevant studies reveals some shortcomings on the DEA method to be carefully addressed. More precisely, the initial stage of DEA is to select proper inputs and outputs that are assumed representative for the performance of Decision-Making Units (DMUs). Thus, the soundness of findings relies on the chosen criteria measuring the operational efficiency of airports. Given the multitude of efficiency measures used in the extant literature, there is no unique set of factors upon which researchers agree [17–21]. In DEA-based applications, the common practice is to select the factors based on the frequency of use in the literature, availability of data, and subjective preferences of stakeholders. Obviously, this requires using a more systematic approach that considers the subjective evaluations on the relevance of the performance measures [22]. For that reason, the present study hybridizes Spherical Fuzzy Sets based Analytic Hierarchy Process (SFS-AHP) with DEA to handle the highly subjective essence of the selection task.

Another drawback of DEA-based studies on airport performance is that they usually neglect the effect of the outliers on the performance scores [17,19,20,23–26], which may be reportedly a crucial complementary part of DEA-based efficiency analysis [27]. The single exception that we determine is a recent study [28], where efficiency scores were reported without outliers. Remarkably, outlier detection requires a careful approach that can cluster extreme DMUs given the multidimensionality (multiple inputs and outputs) of the problem domain. To this end, the present study uses a machine learning based clustering technique, Self Organizing Map (SOM) [29].

Studies on the Turkish airports are very scarce [3,23,25,28]. These studies can be improved in terms of the above-mentioned shortcomings of DEA-based efficiency analysis on airports. With this motivation, the present study investigates the efficiency of the Turkish airports by using an integrated Spherical Fuzzy AHP/DEA technique throughout 2015–2018. To identify the determinants of efficiency, the Tobit regression model is employed to evaluate the impact of different attributes that lead to airport efficiency.

The study contributes to three aspects of the relationship between operational efficiency and airport management strategy. First, we selected DEA input- and output-factors using a novel variant of AHP, SFS-AHP, that provides an appropriate approach to overcome the disadvantages of deterministic AHP. In this way, subjective opinions of different stakeholder groups could be combined, and the most proper efficiency measures may be employed for DEA. Second, we conducted an outlier analysis by utilizing SOM to examine the effect of outlier airports on the efficiency scores obtained by DEA, which is uniquely embedded in an efficiency analysis study on airports. Finally, a posthoc analysis has been held by employing a Tobit regression model to examine the relationship between airports efficiency and the potential explanatory variables i.e., tourism potential, number of international flights, distance to the city center, population, public/private ownership, and age of airport that have been scarcely addressed in the prior studies.

This paper is organized as follows. Section 2 provides a comprehensive review of the extant literature. Section 3 elaborates the suggested methodology and the variables of interest for the analysis, while Section 4 presents the empirical results and provides a detailed discussion. Finally, Section 5 concludes the work and offers possible research areas for new studies.

2. Literature review

In recent years, numerous studies have focused on assessing the efficiency of airports drawing attention to their increasing role in sustainable development from different angles [2,28,30–33]. The topic has gained significant importance with the rapid growth of the air transport industry in developing countries. Many of these studies highlight that higher operational efficiency significantly improves overall airport efficiency and increases their financial performance [33–35].

A study [36] measured the efficiency of 40 Spanish airports and showed that the capacity has a vital role. [37] used DEA to analyze 35 Brazilian airports to evaluate efficiency. A similar DEA approach was adopted by [21] to measure the relative efficiency of Japanese airports and specifically addressed the issue of over-investment. [26] also employed DEA and truncated bootstrapped regression to identify significant factors affecting the efficiency scores of Greek airports obtained with DEA. The study highlighted location, size, and operating characteristics as vital determinants of efficiency. In the Chinese context, [20] investigated the efficiency of 41 airports. The study used the double bootstrap DEA method and indicated that airports located next to large cities are more efficient than regional airports. Another study addressing Chinese airports was conducted in [38], which evaluated 20 major Chinese airports between 2006 and 2009. Similar to the previous research, they concluded that the international airports performed significantly better than the regional airports. A novel approach was proposed in [39] that combined AHP, DEA, and Assurance Region (AR) to assess 24 international airports. They claimed that the DEA-AR combination demonstrated higher discriminatory power than classical DEA. A recent study on the efficiency of Italian airports for a 10-year time period starting from 2006 to 2016 has provided additional insights on the determinants of technical and scale efficiency scores obtained with DEA [19]. The authors reported that airport size, presence of low-cost carriers, and cargo traffic are vital factors. Ennen and Batool [40] examined the efficiency of 12 major airports in Pakistan by using DEA for the year 2012 and indicated that overstaffing and overinvestment on capacity caused cost inefficiencies at several airports. Olariaga and Moreno [41] analyzed airport efficiency in Colombia for 2012–2017, revealing that major airports operated by the private sector had higher efficiency. Stichhauerova and Pelloneova [42] assessed the efficiency of 27 German airports for the year 2016 by employing DEA-CCR (Charnes, Cooper, and Rhodes) and BCC (Banker, Charnes, and Cooper) models [43]. They identified that 13 airports performed technically efficiently by employing the best practices. Ngo and Tsui [18] engaged DEA-Window analysis relying on slack-based measures for evaluating 11 New Zealand airports. The authors showed that tourism, airport privatization, regional economic development, airport's domestic networks, and low-cost carrier services positively affect the efficiency scores. Huynh et al. [33] investigated the efficiency of the Southeast Asia airports by a two-stage approach covering DEA-SBM, and Tobit regression and reported that the decentralizing authority tends to increase efficiency. In a similar study, Liu analyzed East Asian airports by using Network DEA and concluded that airport efficiency was positively influenced by the number of airlines served and destinations [44].

Recent studies aiming to identify the determinants of efficiency from different perspectives have gained new ground. The effect of logistic channels and the intermodality of the transport system was evaluated in [31], where the authors report that every 1% increase in Logistic Performance Index leads to an efficiency improvement of 0.15%, and a High-Speed Rail network serving the airport contributes strikingly to the efficiency scores of airports. The relationship between the ownership, human capital, and the efficiency scores of 12 Polish airports was studied in [30], confirming the relevance of managerial experience gained in the same airport. The authors used time-variant stochastic frontier analysis. Identifying the operational drivers of efficiency is another focal point in recent research. [45] calculated the infrastructure and flight consolidation efficiency of major international airports using DEA. The efficiency drivers were then extracted with quantitative analysis on well-performing airports in the previous stage. The study in [32] addressed the sustainable efficiency of major Euroasian airports considering desirable and undesirable outputs using a novel fuzzy double-frontier network DEA. The results confirm the positive impact of private participation.

When it comes to the efficiency analysis on Turkish airports, the topic has received a relatively high level of attention since the 2010s. Although few studies shed light on Turkish airports' efficiency based on data before 2012 [3,23,46], they are not quite relevant to the current situation of airports in Turkey, as the airport infrastructure were substantially expanded in 2011 with vast investments in the airport infrastructure. Hence, the numbers and capacities of the airports were remarkably increased [25]. Thus, we report only those DEA studies conducted with the data after that year. [25] analyzed the operational performance of 21 Turkish airports for the years 2009–2014 using the Malmquist productivity index, indicating that the operating hours and international traffic were the factors explaining variations in efficiency. This study is also remarkable because it benchmarks the efficiency scores before and after the expansion policy. Keskin and Köksal [46] compared the efficiency of publicly and privately operated airports in Turkey by DEA and AR methods. The study revealed that 14 airports were efficient according to the DEA-BCC and DEA-CCR methods. In contrast, the private sector operated only two efficient airports, and none of the publicly operated airports was efficient according to the AR method. Recently, [28] explored the operational efficiency of 43 Turkish airports for the year 2013 and found that airport efficiency is influenced by the ability of the airports to use their resources more efficiently than external factors.

Overall, these studies provide important insights for airports' performance evaluation based on a wide variety of input and output measures. Accordingly, one may note that there is no single set of criteria due to the subjective nature of the data selection and preparation stage. Thus, a systematic approach that can handle subjectivity, SFS-AHP, as suggested by the present study, is of great help. In addition, the studies presented in this section provide evidence that the outlier analysis did not get the attention it deserved. Here, we employ a machine learning approach, SOM, which can cluster airports on a multidimensional problem domain.

3. Data and methodology

Considering the studies presented in the previous section, DEA is the most commonly used method for measuring efficiencies of airports, while some hybrid techniques were proposed to remedy the drawbacks of DEA. In a similar vein, this study employs a hybrid methodology. In classical DEA studies, the process of determining inputs and outputs is generally executed subjectively by considering the most frequently used factors in the literature. However, this approach has been subject to criticism [22]. Another weak point of the previous DEA studies is that they measure the efficiency of airports without considering outliers. However, extremely large decision-making units may seriously affect efficiency scores [27,47,48]. Since the airports with extreme values cannot be detected by considering a single dimension due to the nature of DEA, SOM is used to cluster multidimensional data [29,49] successfully.

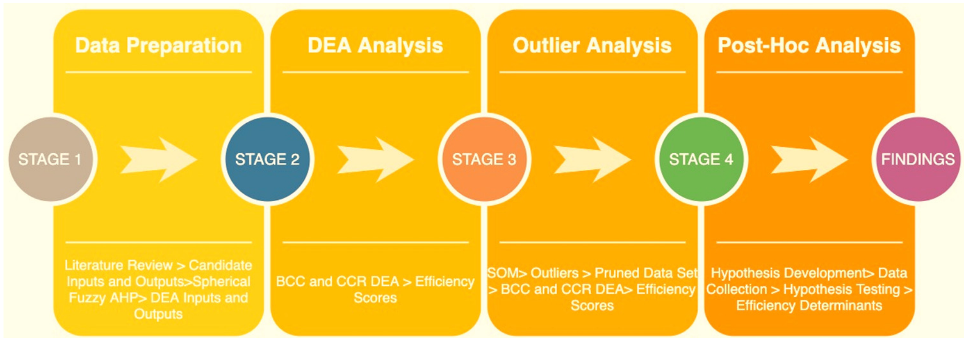


Fig. 1. The conceptual framework.

Considering the aforesaid points, a four-stage approach is followed in this study. In the first stage of data preparation, the inputs and outputs used to measure the performance of airports will be determined based on the literature survey. Then, the relative importance of the factors will be measured with the fuzzy spherical AHP method, which was evaluated by seven experts in the field of airport management. The top-scored factors will be shortlisted for DEA. In the second stage, the selected inputs and outputs will be used to evaluate the performance of the airports in Turkey for the years 2015–2018. In the third stage, we examine how much the DEA performance scores are affected by extreme values. For this purpose, SOM, a multidimensional clustering and outlier detection algorithm, will be employed. Different alternatives will be evaluated to determine the correct SOM architecture by considering Dunn's cluster validity index [49,50]. With the optimal SOM topology, outlier DMUs will be detected and separated. DEA performed in the previous stage will be repeated to answer whether there is any significant difference between the scores. Finally, during the posthoc analysis stage (stage four), the association between the efficiency scores and some potential attributes that are expected to impact the performance of the airports will be examined. The methodological framework is displayed in Fig. 1. Obviously, airports have better control over the outputs due to the fact the input factors, such as terminal utilities, runway, and terminal capacities, are usually determined by the public authorities. Thus, we assume input factors as given and use the output-oriented DEA. Throughout our work, we used MS Excel for storing and editing data for other platforms, DEAP [51] and IBM SPSS v25. MS Excel was employed for data preparation and SF-AHP weights. The scores of DEA were calculated with DEAP [51], while MATLAB and IBM SPSS v25 were used for outlier detection and posthoc analysis, respectively.

3.1. Spherical Fuzzy sets: Preliminaries

The deterministic AHP method is criticized for its incapability to handle uncertainty in human judgments [52]. In this study, we used a novel variant of AHP, spherical fuzzy sets (SFS), based on the AHP method that offers an appropriate approach to overcome the disadvantages of AHP, the lack of capturing indeterminacy of information. SFS defines a membership function on a spherical surface, which enables assigning the parameters of the membership function on a larger domain independently for various types of uncertainty [53,54]. In SFS, the squared sum of membership, non-membership, and hesitancy parameters can be between zero and one. Furthermore, each can be projected independently to a domain to satisfy that their squared sum is at most equal to one.

The following section presents the preliminaries on SFSs. The reader may refer to [54] for more details on SFSs.

Definition 1. SFS, $\tilde{A}_s$, of the universe of discourse U is defined by the following expression;

$$u_{\tilde{A}_s}: U \to [0,1],\ v_{\tilde{A}_s}: U \to [0,1],\ \pi_{\tilde{A}_s}: U \to [0,1]$$

and

$$0 \le u^2_{\tilde{A}_s}(u) + v^2_{\tilde{A}_s}(u) + \pi^2_{\tilde{A}_s}(u) \le 1 \quad (u \in U),$$
$$\tilde{A}_s = \left\{ \left\langle u, \left(u_{\tilde{A}_s}(u), v_{\tilde{A}_s}(u), \pi_{\tilde{A}_s}(u) \right) \right\rangle | u \in U \right\}.$$

The values, $u_{\tilde{A}_s}(u), v_{\tilde{A}_s}(u),$ *and* $\pi_{\tilde{A}_s}(u)$ are the degree of membership, non-membership, and hesitancy of u to $\tilde{A}_s$, respectively.

Definition 2. The basic operations on SFSs are defined as follows:

Addition:

$$\tilde{A}_s \oplus \tilde{B}_s = \left\{ \sqrt{u^2_{\tilde{A}_s} + u^2_{\tilde{B}_s} - u^2_{\tilde{A}_s}.u^2_{\tilde{B}_s}},\ v_{\tilde{A}_s}.v_{\tilde{B}_s},\ \sqrt{\left(\left(1 - u^2_{\tilde{B}_s}\right)\pi^2_{\tilde{A}_s} + \left(1 - u^2_{\tilde{A}_s}\right)\pi^2_{\tilde{B}_s} - \pi^2_{\tilde{A}_s}.\pi^2_{\tilde{B}_s} \right)} \right\}$$

Multiplication:

$$\tilde{A}_s \bigotimes \tilde{B}_s = \left\{ u_{\tilde{A}_s}.u_{\tilde{B}_s},\ \sqrt{v^2_{\tilde{A}_s} + v^2_{\tilde{B}_s} - v^2_{\tilde{A}_s}.v^2_{\tilde{B}_s}},\ \sqrt{\left(\left(1 - v^2_{\tilde{B}_s}\right)\pi^2_{\tilde{A}_s} + \left(1 - v^2_{\tilde{A}_s}\right)\pi^2_{\tilde{B}_s} - \pi^2_{\tilde{A}_s}.\pi^2_{\tilde{B}_s} \right)} \right\}$$

Multiplication by a scalar:

$$x.\tilde{A}_s = \left\{ \sqrt{1 - \left(1 - u^2_{\tilde{A}_s}\right)^x},\ v^x_{\tilde{A}_s},\ \sqrt{\left(1 - u^2_{\tilde{A}_s}\right)^x - \left(1 - u^2_{\tilde{A}_s} - \pi^2_{\tilde{A}_s}\right)^x} \right\}$$

x Power of $\tilde{A}_s$:

$$\tilde{A}^x_s = \left\{ u^x_{\tilde{A}_s},\ \sqrt{1 - \left(1 - v^2_{\tilde{A}_s}\right)^x},\ \sqrt{\left(1 - v^2_{\tilde{A}_s}\right)^x - \left(1 - v^2_{\tilde{A}_s} - \pi^2_{\tilde{A}_s}\right)^x} \right\}$$

Table 1
Linguistic scale and its Score Index and its corresponding SF Sets.

	Score Index (SI)	(u, v, π)
Absolutely more importance(AMI)	9	(0.9,0.1,0.0)
Very high importance (VHI)	7	(0.8,0.2,0.1)
High importance (HI)	5	(0.7,0.3,0.2)
Slightly more importance (SMI)	3	(0.6,0.4,0.3)
Equally importance (EI)	1	(0.5,0.4,0.4)
Slightly low importance (SLI)	1/3	(0.4,0.6,0.3)
Low importance (LI)	1/5	(0.3,0.7,0.2)
Very low importance (VLI)	1/7	(0.2,0.8,0.1)
Absolutely low importance (ALI)	1/9	(0.1,0.9,0.0)

Union:

$$\tilde{A}_s \cup \tilde{B}_s = \Big\{ \max(u_{\tilde{A}_s}, u_{\tilde{B}_s}), \min(v_{\tilde{A}_s}.v_{\tilde{B}_s}), \min\Big(1 - \Big(\big(\max\big(u_{\tilde{A}_s}, u_{\tilde{B}_s}\big)\big)^2 + \big(\min\big(v_{\tilde{A}_s}, v_{\tilde{B}_s}\big)\big)^2\Big), \max(\pi_{\tilde{A}_s}, \pi_{\tilde{B}_s})\Big)\Big\}$$

Intersection:

$$\tilde{A}_s \cap \tilde{B}_s = \Big\{\min(u_{\tilde{A}_s}, u_{\tilde{B}_s}), \max(v_{\tilde{A}_s}.v_{\tilde{B}_s}), \min\Big(1 - \Big(\big(\min\big(u_{\tilde{A}_s}, u_{\tilde{B}_s}\big)\big)^2 + \big(\max\big(v_{\tilde{A}_s}, v_{\tilde{B}_s}\big)\big)^2\Big), \min(\pi_{\tilde{A}_s}, \pi_{\tilde{B}_s})\Big)\Big\}$$

Definition 3. Spherical Weighted Arithmetic Mean (SWAM) with respect to, $w = (w_1, w_2, \ldots, w_n)$ and $\sum_{i:1}^{n} w_i = 1$, is defined as follows:

$$SWAM_w(\tilde{A}_{s1}, \tilde{A}_{s2}, \ldots, \tilde{A}_{sn}) = w_1\tilde{A}_{s1} + w_2\tilde{A}_{s2} + \cdots + w_n\tilde{A}_{sn}$$
$$= \left\{ \sqrt{1 - \prod_{i=1}^{n}\left(1 - u^2_{\tilde{A}_{si}}\right)^{w_i}}, \prod_{i=1}^{n} v^{w_i}_{\tilde{A}_{si}}, \sqrt{\prod_{i=1}^{n}\left(1 - u^2_{\tilde{A}_{si}}\right)^{w_i} - \prod_{i=1}^{n}\left(1 - u^2_{\tilde{A}_{si}} - \pi^2_{\tilde{A}_{si}}\right)^{w_i}} \right\}$$

To determine the weights of performance criteria, SFS-AHP comprises four steps defined based on the definitions given above.

Step 1: Construct the hierarchical structure, that is, to define the candidate inputs and outputs for the efficiency evaluation of airports.

Step 2. Given the linguistic terms given in Table 1, construct a pairwise comparisons matrix (Gündoğdu and Kahraman, 2019). Then, Eqs. (1) and (2) are used to obtain the score indices (SI) in Table 1.

For AMI, VHI, HI, SMI, and EI

$$SI = \sqrt{\left|100 \times \left(\left(u_{\tilde{A}_s} - \pi_{\tilde{A}_s}\right)^2 - \left(v_{\tilde{A}_s} - \pi_{\tilde{A}_s}\right)^2\right)\right|} \quad (1)$$

whereas for reciprocal indices;

$$SI^{-1} = \frac{1}{\sqrt{\left|100 \times \left(\left(u_{\tilde{A}_s} - \pi_{\tilde{A}_s}\right)^2 - \left(v_{\tilde{A}_s} - \pi_{\tilde{A}_s}\right)^2\right)\right|}} \quad (2)$$

Step 3. Estimate the main and sub-criteria's spherical fuzzy global and local weights, respectively. This is done with SWAM in Definition III. Finally, the weighted arithmetic mean needs to be computed for the spherical fuzzy weights.

3.2. Evaluation of airport efficiencies with DEA

Before applying DEA, a survey for FSF-AHP was sent to the experts on airport management by e-mail to select the most proper inputs and outputs. We sent ten questionnaires and received seven of them, a response rate of 70%. We use DEA model based on the selected input and output measures.

DEA is a technique introduced in [55] to measure the relative efficiency of DMUs. In DEA, input and output factors are used to construct a production frontier for a set of comparable DMUs, which defines a relative efficiency benchmark for the target DMU based on the distance. This study utilizes the DEA-BCC model as it allows distinguishing technical and scaling inefficiencies. DEA provides the following advantages: Firstly, it assigns a score to each DMU and enables the analyst to build a solid ranking. Secondly, it provides a recipe for inefficient REITs by outlining how the efficiency of a certain DMU improved with a marginal change in the input or output domains.

According to the conventional DEA, the efficiency of a DMU can be evaluated from two angles: input-oriented and output-oriented DEA. The first one assumes the control of the management is on the inputs, whereas the latter indicates that the performance of a DMU is mainly manipulated by the output factors. To conduct the efficiency analysis on the airports, we used the output-oriented DEA-BCC model [43] because the airport managements have more control over the outputs than the inputs as the input production factors are usually determined by policymakers and the public authorities rather than airport operators.

DEA solves a linear programming problem for each DMU under consideration so that an efficiency score can be assigned to it.

Given n DMUs, each being evaluated with r inputs and s outputs. The data for evaluation is given as $\boldsymbol{X}$, a *rxn* matrix of input factors, and $\boldsymbol{Y}$, a *sxn* matrix of output factors. For the qth DMU, the inputs and outputs are defined with two vectors, $\boldsymbol{x_q}$, and $\boldsymbol{y_q}$, respectively. The efficiency score of each DMU is calculated by maximizing the ratio of outputs to inputs under the assumption all DMUs build an envelope. However, the initial form of the problem is not linear. A dual linear equivalent of the problem is formulated to overcome this burden. To obtain the efficiency score θ_q for DMU_q, the following output-oriented dual linear programming problem is solved [51] (see Eqs. (3)–(7)):

$$\max_{\theta,\boldsymbol{\lambda}} \theta_q \quad (3)$$

$$\text{s.t.} \ -\theta_q y_q - \boldsymbol{Y\lambda} \geq 0 \quad (4)$$

$$x_q - \boldsymbol{X\lambda} \geq 0 \quad (5)$$

$$\boldsymbol{B^T\lambda} = 1 \quad (6)$$

$$\boldsymbol{\lambda} \geq 0 \quad (7)$$

where $1 \leq \theta_q \leq \infty$ is a scalar to be determined, $\boldsymbol{\lambda} = [\lambda_1, \ldots, \lambda_n]$ is an n-dimensional vector of dual variables, and $\boldsymbol{B}$ is an n-dimensional vector of ones. That is, Eq. (6) implies that the sum of the elements of the vector, $\boldsymbol{\lambda}$, is equal to one. The problem with Eq. (6) is called variable return to scale formulation of DEA, whereas the formulation without Eq. (6) is for constant return to scale and assumes DMUs are operating at optimal scale [51]. Note that $1/\theta_q$ gives a technical efficiency score between zero and one, which will be also reported in this paper.

3.3. Self Organizing Maps (SOM)

SOMs are a special type of artificial neural network used for data clustering and representation [29,56]. The method has been preferred as an unsupervised machine learning technique for the complex dimensional presentation of a dataset in hybrid

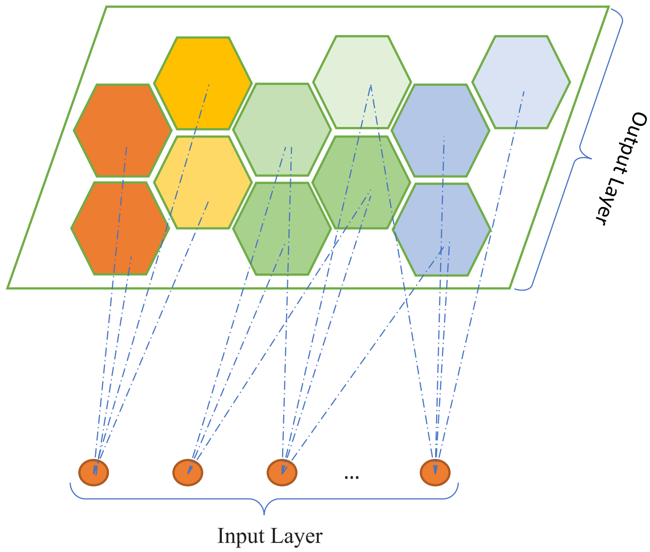


Fig. 2. A standard SOM layout.

decision-making problems. By employing this technique, it will be possible to visualize the high-dimensional data to observe engineering problems [29,57]. A SOM consists of an input layer and a two-dimensional Kohonen layer. The nodes in the input layer are the input data variables (or properties), while the nodes in the output layer represent clusters.

Unlike other artificial neural networks, in Kohonen networks, the alignment of neurons in the output layer is quite important. Assuming that there is m number of variables and n number of nodes (clusters), the distance of each pair of nodes is calculated. SOM can reduce a multidimensional dataset into two dimensions. This allows the entire data set to be quickly evaluated by decision-makers. In the training process of SOM, neurons compete with each other. At the end of the training process, similar samples containing same/similar patterns will be represented in the same neurons (see Fig. 2).

Different cluster validity indices are used to evaluate the suitability of the cluster divisions obtained by SOM. The Dunn index (DI) is only one of these [58]. The main objective of DI is to obtain the best topology that provides the largest ratio between the smallest inter-cluster distance and the largest in-cluster distance. The topology with the largest DI will give the best clustering (Eq. (8)). We will compare various clustering topologies using DI.

$$DI = \min_{1\leq i\leq n}\left\{\min_{1\leq j\leq n}\left\{\frac{d\left(c_i, c_j\right)}{\max_{1\leq k\leq n}\left\{d'\left(c_k\right)\right\}}\right\}\right\}, \quad i \neq j \tag{8}$$

Even though it is a practical and widely used technique in engineering problems, few studies employ the SOM in the aviation industry [59,60]. Therefore, this study will also significantly contribute to the related literature of the aviation industry by utilizing the SOM technique to examine the effect of outlier airports on the efficiency scores.

Kumar's study on SOM neural networks for air space sectoring demonstrated that the computation of automatic balanced sectoring of airspace increases air traffic control capacity in high-density traffic airspace [59]. Chen and colleagues developed a reliability prediction model of aircraft using SOM technique to help proactively diagnose spare parts faults with a sufficient lead time. This method aims to prevent actual system failures with timely scheduled preventive maintenance while reducing the downtime cost [60].

Furthermore, there is no significant study that blends SOM and AHP techniques in the aviation industry except Zhao and Chen's study [61]. Their study hybridized both techniques for data analytics in the aviation industry to demonstrate how SOM and AHP techniques accurately and effectively classify and evaluate the competitiveness of airlines and the efficient allocation of traffic rights resources [61].

4. Empirical findings

4.1. Results of spherical fuzzy AHP and sample selection

Our sample covers 46 Turkish airports for the period of 2015–2018. Out of 46 airports, the private sector operates seven of them, while the public sector operates the remaining ones. We had to exclude the recently built airports as no data is available. The list of the airports is given in the Appendix (see Table A.1).

After the sample selection, we conducted the variable selection procedure. We drew the most frequently used performance measures based on the extensive literature review. Nine inputs and four outputs were taken into consideration to be evaluated with the SFS-AHP method, which is a mix of capacity, financial, and service measures. The problem hierarchy is depicted in Fig. 3. Based on the subjective evaluations collected from seven experts in airport management. If the consistency index is less than 0.10 for the pairwise comparison matrix obtained from the experts, then this questionnaire was considered acceptable. Then, we calculated normalized SFS-based weights for the inputs and outputs. The fuzzy values are then defuzzified, and the items were ranked in decreasing order based on the relevance scores. Figs. 4 and 5 depict the defuzzified relevance scores of the candidate inputs and outputs. Accordingly, we used *terminal capacity in square meters (0.1427), runway capacity (length of the runway) in meters (0.1358),* and *total expenditures (in TL) (0.1270)* as inputs, while the *number of passengers (0.2782), total revenues (0.2718), and cargo volume (0.2598)* are selected as outputs. The data set covers both domestic and international traffic.

The size of runways and terminals shapes the handling capacities of airports. *Runway capacity* is important in airport infrastructure and makes it possible for different sizes of aircraft to land. Some Turkish airports, particularly in smaller cities, have short runways, making it impossible for larger aircraft to land. *Terminal size* reflects the number of passengers that could be annually handled, which can be linked to the quality of services and satisfaction of the passengers. Finally, we used a more generic input factor, *total expenditures*. Some other recent studies have also recognized the selected candidate variables [62–65].

We used *the number of passengers* as the first output. It reflects the volume of operations and hence, the actual use of airport infrastructure. We did not use the number of aircraft movements as an output since it is a similar performance indicator. *Airport total revenues* was the second output. For this output, we did not differentiate between aeronautical revenues, i.e., passenger fees, landing and parking fees, and non-aeronautical revenues, i.e., rents, car parking, and other services, since both types can effectively be manipulated by airport management. The third output is the *cargo volume* reflecting another significant revenue-generating activity of the airports. The literature has also emphasized the importance of the selected outputs [19,26,28,39].

To measure airport efficiency, we used TGDSA as the primary data source. We collected the data for the input and output variables from TGDSA annual reports, whereas the data on the explanatory variables, i.e., tourist traffic and population, were obtained from annual reports published by the Turkish Statistical Institute. Table 2 summarizes the descriptive statistics of the input and output variables over the evaluation period (2015–2018). We also applied a Spearman rank-order correlation analysis to find out the relationships between the inputs and outputs. Table 3 presents the results. All the correlation coefficients are positive, meaning that an output does not decrease with an increased input.

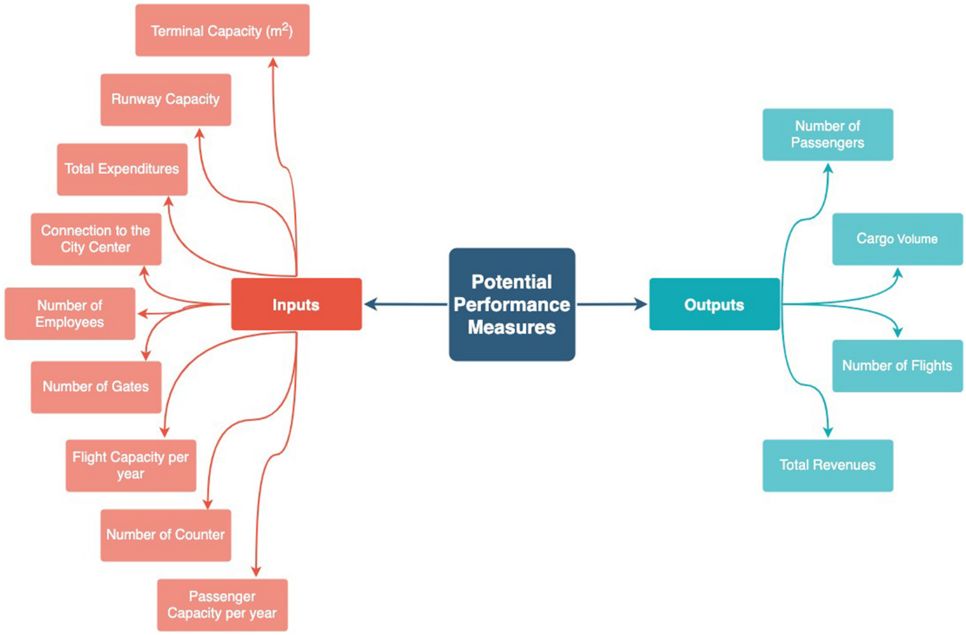


Fig. 3. Potential performance measures for Turkish airports.

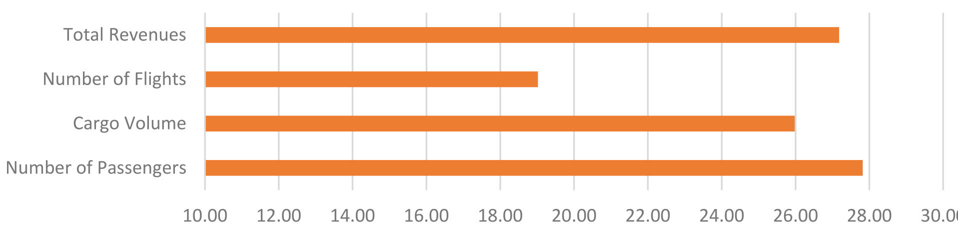


Fig. 4. Defuzzified relevance scores of candidate outputs.

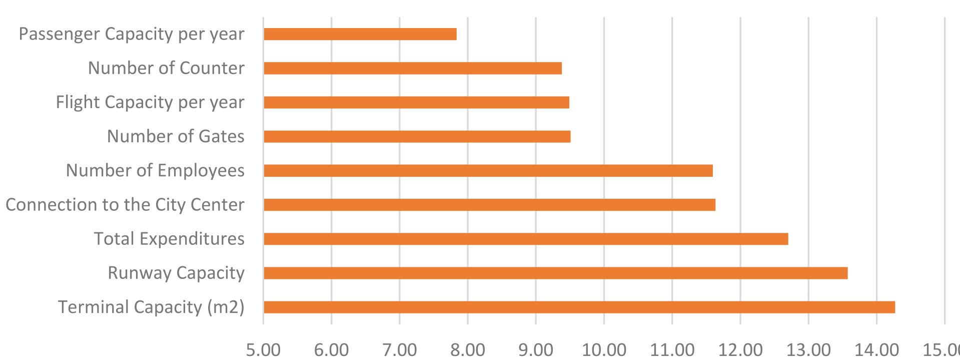


Fig. 5. Defuzzified relevance scores of candidate inputs.

Table 2
The summary of descriptive statistics.

	Outputs			Inputs		
	Number of passengers	Cargo traffic (tons)	Total revenues (k TRY)	Runways (m^2)	Terminal size (m^2)	Total expenditures (k TRY)
Min	20,876	0	30	90,000	380	4,253
Max	68,346,784	1,281,186	3,454,705	440,550	135,634	679,213
Mean	4,186,967	24,740	110,224	168,068	16,631	57,982
SD	10,905,003	147,046	388,029	80,984	29,414	87,378

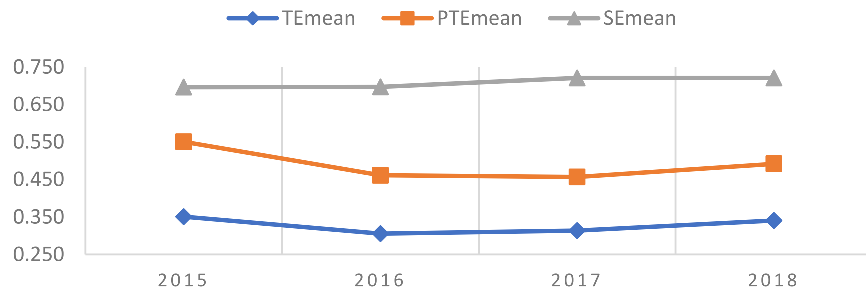


Fig. 6. Average TE, PTE, SE scores for 2015–2018.

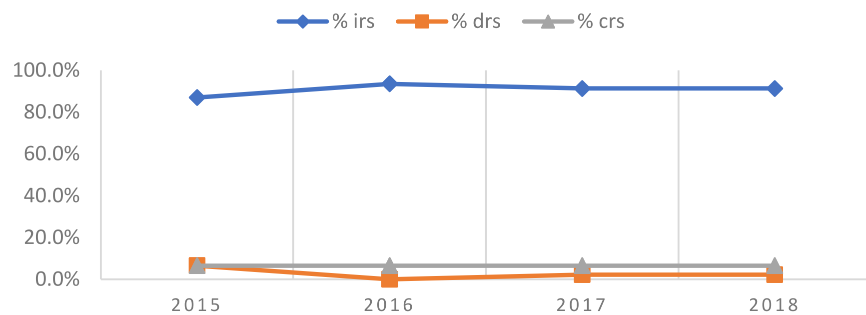


Fig. 7. Percentage of airports facing IRC, DRS, and CRS conditions.

Table 3
Correlation matrix.

Input variables	Output variables		
	Number of passengers	Cargo traffic (tons)	Total revenues (k TRY)
Runways (m^2)	0.663**	0.477**	0.655**
Terminal size (m^2)	0.896**	0.630	0.750**
Total expenditures (k TRY)	0.865**	0.675**	0.871**

**Correlation is significant at the 0.01 level (2-tailed).

4.2. Efficiency analysis with DEA

Table 4 reports the average efficiency scores of the selected airports for each year, while Fig. 6 gives the mean Technical Efficiency (TE), Pure Technical Efficiency (PTE), and Scale Efficiency (SE) scores for the entire sample. The results in Table 4 show that most of the airports in the sample have not performed well from 2015 to 2018, particularly in 2016, with an annual average TE and PTE scores of 0.328 and 0.461, respectively. These results indicate that the CRS-frontier envelops 93.5% of Turkish airports and, thus, they are subject to varying degrees of inefficiency. This finding is in line with the results of [25,28]. One explanation may be related to the poor management of the available resources by the airport managers during this interval. Although Turkish airports have expanded and have been equipped with modern equipment and services, airport managers have not shown the required ability to use these resources and implement appropriate policies to handle operational and structural changes.

Overall, SE scores suggest that 93.5% of the airports should spend considerable efforts to refine their operations by implementing managerial and structural changes to reduce input factors for the majority of the airports. Furthermore, DEA findings indicate that the selected Turkish airports have been operated at about 67.2% below their optimal efficiencies under the constant returns to scale (CRS) assumption, that is, they operate in the optimal scale. Considering PTE values, 18.5% of the airports are operating on the efficient frontier. PTE and SE scores show that reported inefficiencies may be primarily attributed to the operational practices (overall mean PTE = 0.490), while economies/diseconomies of scale issue (overall mean SE = 0.709) is less important.

Table A.1 in the Appendix displays the individual PTE scores of the airports for the period of 2015–2018. It is apparent that very few airports enjoy operational efficiency; Istanbul Atatürk, Istanbul Sabiha Gokcen, Adana, Amasya Merzifon, Kahramanmaraş, Sinop, and Uşak are the efficient airports, whereas Bursa Yenişehir, Balı kesir Kocaseyit, Erzincan, Tekirdağ Çorlu, and Denizli Çardak are the five least efficient DMUs in the sample. Most efficient airports are usually characterized by the comparatively low capacity of infrastructural facilities that allows them efficient utilization of the resources and high international traffic. However, some of these findings contradict the results in [28]. For example, they reported only Istanbul Atatürk and Bingöl airports as being efficient ones, while the five least efficient airports were listed as Ankara Esenboğa, Adana, İzmir, Erzurum, and Bursa Yenişehir based on the PTE scores [28]. This somewhat contradictory result may be due to the different time-period and different set of factors they used: labor and total expenditures as inputs and total revenues as output.

When we decompose TE scores into PTE and SE values, it seems that the industry would have increased its average efficiency if the airports had operated at an optimal scale. However, despite the relatively high SE score, an average of 93.5% of Turkish airports practice inconvenient policies regarding the scale and still have some improvement opportunities to explore. A closer look at Table 4 and Fig. 7 reveals that most of the airports (overall mean 90.8%) are subject to increasing returns to scale (IRS) condition, that is, the scale inefficient airports may increase their outputs more than double if the input factors double. Namely, an expansion on the infrastructure of the airports may lead to an efficiency increase. Likewise, [28] reported a similar condition based on the SE scores of the Turkish airports in 2013.

On the other hand, decreasing returns to scale (DRS) condition appeared only once for Antalya airport, which seems to be slightly too big to be scale efficient with an average SE of 0.945 over the entire period. In addition, the airport operates close to the efficient frontier with an average PTE score of 0.846. The SE results

Table 4
Summary of efficiency analysis on the Turkish airports.

Year	TE_{mean}	PTE_{mean}	SE_{mean}	*% of TE efficient DMUs*	*% of PTE efficient DMUs*	*% of SE efficient DMUs*	*% of irs*	*% of drs*	*% of crs*
2015	0.351	0.551	0.696	6.5%	21.7%	6.5%	87.0%	6.5%	6.5%
2016	0.306	0.461	0.697	6.5%	17.4%	6.5%	93.5%	0.0%	6.5%
2017	0.314	0.457	0.721	6.5%	17.4%	6.5%	91.3%	2.2%	6.5%
2018	0.341	0.492	0.721	6.5%	17.4%	6.5%	91.3%	2.2%	6.5%
Mean	0.328	0.490	0.709	6.5%	18.5%	6.5%	90.8%	2.7%	6.5%

also show that the efficiency of Turkish airports may be increased by marching towards the optimum scale, while improvements in the utilization of resources must be another focal point.

On temporal dimension, we observe a fairly stable and stationary series with limited fluctuations from 2015 to 2018. However, what is striking in Fig. 6 is the considerably lower average efficiency of the airports during the year 2016. This can be associated with the condemned terror attack in Istanbul Ataturk Airport and the military coup attempt, which took place in June 2016, and July 2016, respectively. These two grievous events caused devastating consequences on Turkish tourism, which, in turn, hampered the civil aviation sector. As a result, in 2016, international visitors were slightly above 25 million, representing a sharp decline by 30% compared to 2015.

Fig. 8 illustrates the distribution of individual performance scores for each year. The left-skewed bell shapes indicate a low number of efficient airports, confirming that a non-negligible portion of DMUs demonstrates poor performance, achieving efficiency scores of 0.5 and below. A mapping in Fig. 9 visualizes the efficiency scores of the individual airports, which confirms that efficiency scores are evenly distributed over the entire country. Thus, the scores may not be associated with regional differences.

4.3. Clustering with SOM and the outlier effect

The use of DEA may lead to problems in the presence of outliers. The outliers may negatively influence the efficiency scores [66]. Therefore, after performing the primary analysis, we ran an outlier analysis to observe the effect of outliers on the efficiency scores as the latter may be extremely sensitive to the outliers [67]. In this context, we make evaluations by eliminating exceptionally large airports. To do this, we used three indicators, cargo traffic (in ton), number of passengers, and number of flights, which reflect the operational scale of the selected sample airports. We aim to detect and separate outlier DMUs with the optimal SOM topology.

We used SOM and evaluated various SOM topologies. To cluster 46 airports, it is expected that the optimal number of clusters will be between 4 (46 * 10% is rounded down to the next integer) and 7 (square root of 46 is rounded up to the next integer) [68]. For this purpose, all two-dimensional topologies have been investigated with cluster numbers between four and seven, namely, 1×4, 1×5, 1×6, 1×7, 2×2, and 3×2. Fig. 10(a) shows the DI values for different topologies. Accordingly, the best clustering topology is selected as 2×2 led to four clusters.

The outlier analysis flagged five outliers in the data set: Istanbul Atatürk, Istanbul Sabiha Gokcen, Esenboğa Airport, İzmir Adnan Menderes Adana Airport, while the remaining 41 airports are placed in a separate cluster (Fig. 10(b)). Fig. 11 illustrates the clustering of 46 airports based on three indicators, i.e., the total number of commercial flights, total number of passengers, and cargo traffic in the outlier analysis, over the entire evaluation period. Therefore, Fig. 10 confirms the SOM clustering.

We re-ran the DEA-BBC model for 41 airports after eliminating the identified outliers. The new analysis yielded remarkably different results, as shown in Table 5. When we remove the outliers from the sample, the number of efficient airports increases, covering 21% of the sample. However, we still observe a decrease in the percentage of efficient airports from 2015 to 2017. As observed in the original sample, most of the new sample (92.7%) also suffers from IRS condition. Fig. 12 compares the percentage of pure technically efficient airports with and without the outliers where a slight increase is observable. Thus, we can conclude that the effect of the outliers on the efficiency scores remained limited. Hence, we employed the efficiency scores obtained without eliminating the outliers for the posthoc analysis.

4.4. Post-Hoc analysis: Tobit regression

We conducted a second-stage regression analysis to explain the previous DEA efficiency scores. Following [69], we run the Tobit regression model. Then, drawing on the earlier studies and data availability, we regressed the DEA efficiency scores on six explanatory variables: number of tourists, number of international flights, distance to the city center, city population, age of the airport, and operator type (public/private).

The cross-firm u_i (random effect) and time (unique effect) errors v_{it} are controlled in the panel data set by using the following random-effects Tobit regression model:

$$y_{it} = \alpha + \beta_1 TOURISTS_{it} + \beta_2 INTFLIGHTS_{it} + \beta_3 DISTANCE_{it} + \beta_4 POPULATIONi_{it} + \beta_5 AGE_{it} + \beta_6 PUBLIC\_PRIVATE_{it} + v_{it} + u_i$$

where y_{it} is the efficiency score (for either TE, PTE, or SE) of the airport i in the relevant year t, $TOURISTS_{it}$ represents the number of tourists, $INTFLIGHTS_{it}$ represents the number of international flights, $DISTANCE_{it}$ represents the distance to the city center, $POPULATION_{it}$ represents the population of the city, AGE_{it} represents the age of the airport and $PUBLIC\_PRIVATE_{it}$ is the operator type (public/private). The impact of the private sector involvement is examined by including a dummy variable in the regression, which takes the value of one when an airport has private involvement and zero otherwise. TOURISTS, INTFLIGHTS, DISTANCE, and POPULATION variables were normalized/scaled using natural logarithms. The descriptive statistics are summarized in Table 6.

Tobit panel data model investigates the statistical relationship between efficiency scores and explanatory variables. The random-effects Tobit panel data model results are presented in Table 7. The results show the significance and magnitude of the impact of explanatory variables on the efficiency scores.

The most significant explanatory variables affecting PTE and TE are TOURISTS and DISTANCE. The POPULATION and AGE significantly affect TE and SE, but no significant impact on PTE. The results in Table 7 show that most of the variation comes from the between-system variation (σu), which is not unexpected. Most of the explanatory variables have not changed much over time. A random-effect Tobit model captures this between-system variation well and validates its use in this context.

Tobit regression model delivers positive and statistically significant results for the number of tourists. The results suggest that the airports located in high-density touristic areas are expected to achieve higher efficiency levels than areas with less

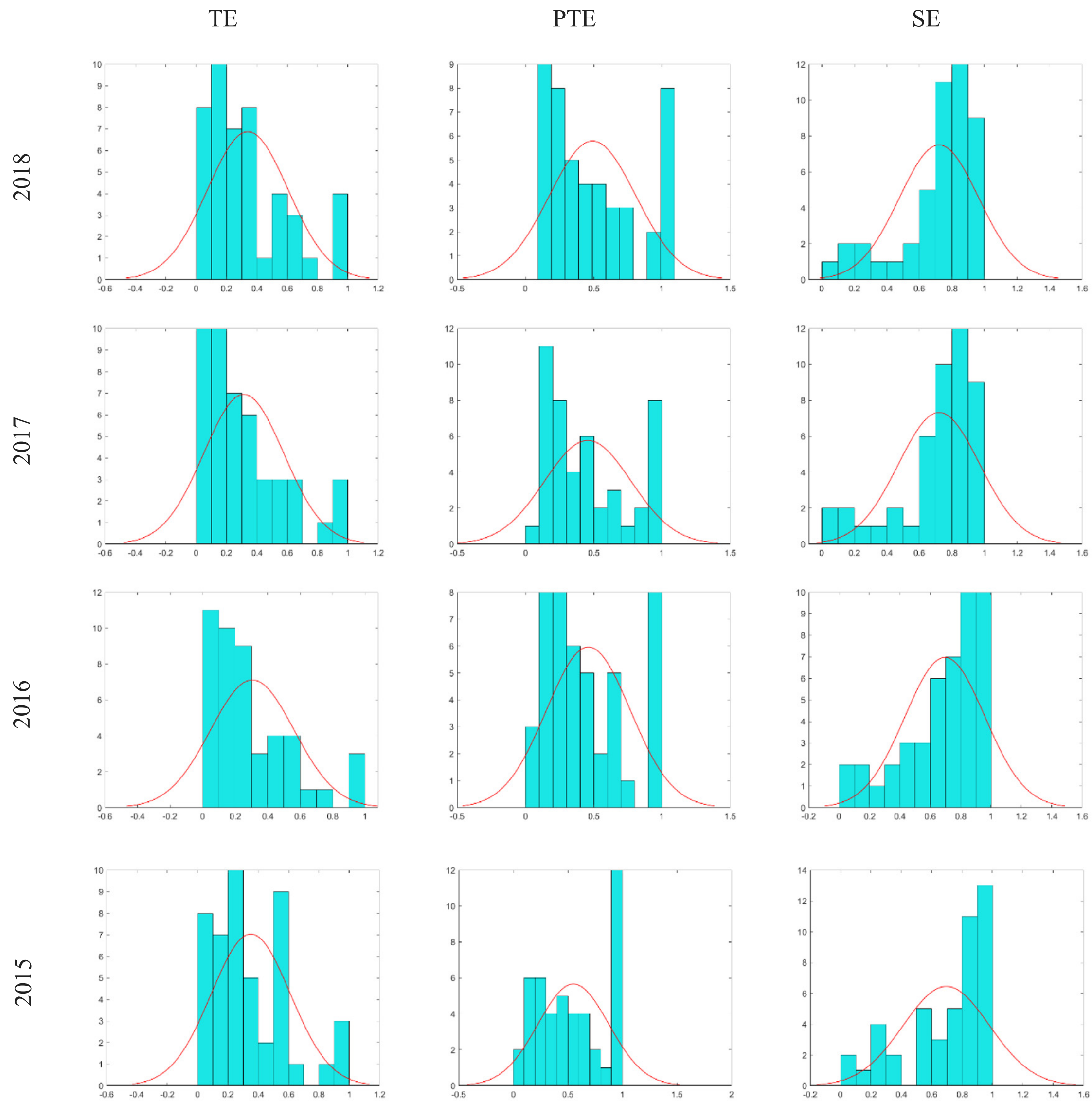


Fig. 8. Distribution of TE, PTE, and SE scores (2015–2018).

Fig. 9. Mapping of the average efficiency scores for Turkish airports.

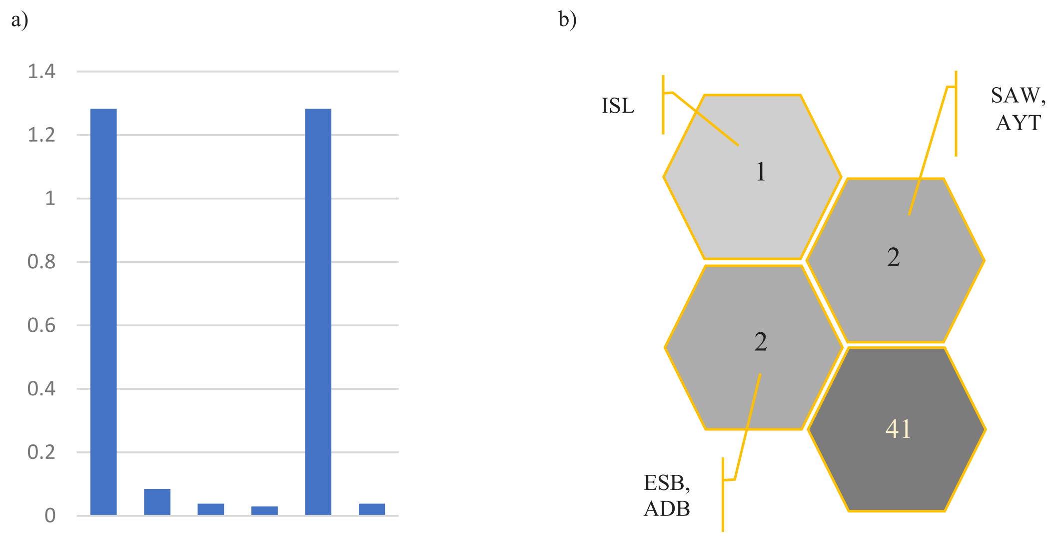


Fig. 10. (a) DI values for candidate topologies, (b) Clustering topology of 46 airports.

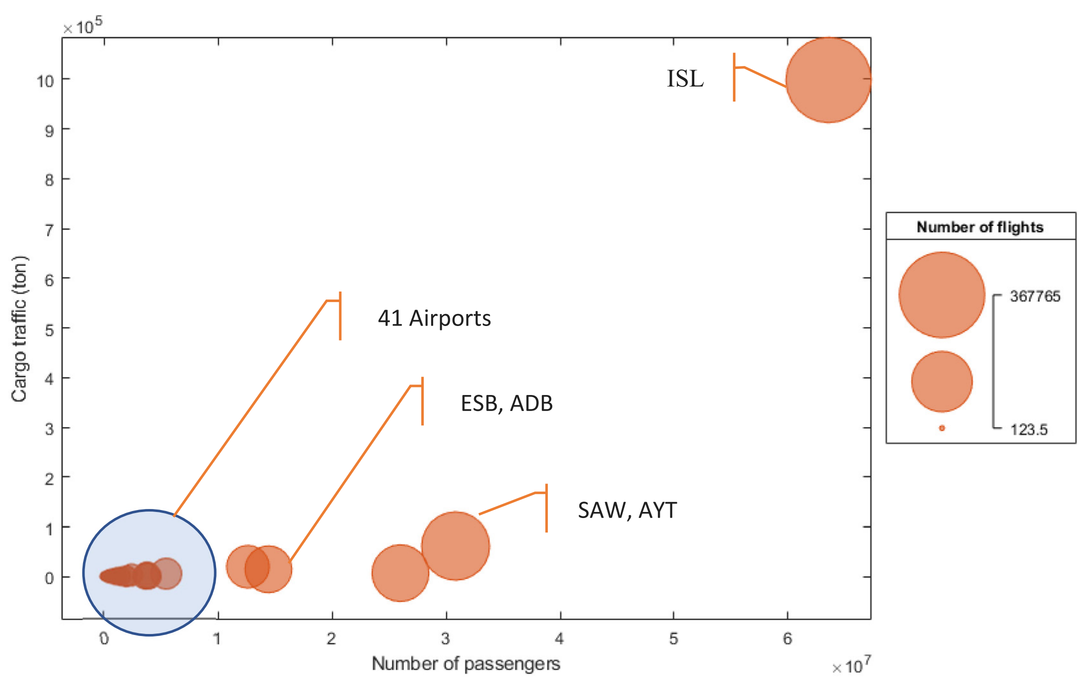


Fig. 11. Bubble chart representation of outlying airports.

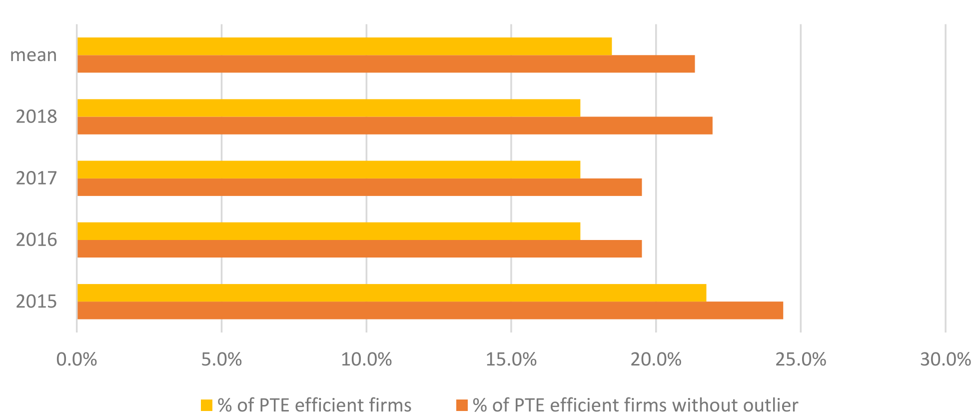


Fig. 12. Comparison of the percentage of pure technical efficient airports with and without the outliers.

Table 5
Summary of efficiency analysis on the Turkish airports without the outliers.

Year	TE_{mean} without outliers	PTE_{mean} without outliers	SE_{mean} without outliers	% of TE efficient firms without outliers	% of PTE efficient firms without outliers	% of SE efficient firms without outliers	% irs without outliers	% drs without outliers	% crs without outliers
2015	0.364	0.598	0.679	4.9%	24.4%	4.9%	92.7%	2.4%	4.9%
2016	0.331	0.532	0.650	4.9%	19.5%	4.9%	92.7%	2.4%	4.9%
2017	0.355	0.545	0.670	4.9%	19.5%	4.9%	92.7%	2.4%	4.9%
2018	0.383	0.575	0.685	4.9%	22.0%	4.9%	92.7%	2.4%	4.9%
Mean	0.358	0.563	0.671	4.9%	21.3%	4.9%	92.7%	2.4%	4.9%

Table 6
Descriptive statistics for the explanatory variables in the Tobit model (2015–2018).

Explanatory variable	Obs.	Mean	Std. Dev.	Min	Max
PTE	184	0.490	0.316	0.053	1.000
TE	184	0.328	0.261	0.021	1.000
SE	184	0.709	0.259	0.021	1.000
TOURISTS	184	11.902	1.879	6.402	16.741
INTFLIGHTS	184	4.713	3.341	0.000	12.680
DISTANCE	184	2.912	0.858	1.386	4.543
POPULATION	184	13.764	0.981	12.168	16.528
AGE	184	28.174	23.032	0.000	81.000
PUBLIC_PRIVATE	184	0.152	0.360	0.000	1.000

Table 7
Second-stage random effects of Tobit regression model results based on DEA scores.

	PTE	TE	SE
TOURISTS	0.065	0.040	0.013
	(0.024)***	(0.014)***	(0.014)
INTFLIGHTS	−0.019	−0.004	0.008
	(0.012)	(0.007)	(0.007)
DISTANCE	−0.134	−0.081	0.037
	(0.052)***	(0.031)***	(0.032)
POPULATION	−0.026	0.073	0.101
	(0.047)	(0.029)**	(0.028)***
AGE	0.000	0.003	0.004
	(0.002)	(0.001)**	(0.001)***
PUBLIC_PRIVATE	0.168	0.087	−0.082
	(0.157)	(0.096)	(0.095)
Constant	0.524	−0.995	−1.089
	(0.629)	(0.383)***	(0.374)***
σ_u Constant	0.258	0.158	0.159
	(0.030)***	(0.018)***	(0.018)***
σ_e Constant	0.139	0.084	0.079
	(0.008)***	(0.005)***	(0.005)***
Number of groups	46	46	46
Observations per group	4	4	4

Notes: Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

tourism density. Thus, tourism inserts a productive externality and acts as a stimulator, particularly by the involvement of low-cost carriers. This result is in line with the findings of previous studies [70,71], where the share of international traffic was a vital factor to explain the efficiency scores. The regression result shows a negative but insignificant relationship for international flights. The negative coefficient shows that a higher share of international traffic has an adverse effect on efficiency due to the more sophisticated infrastructure and facilities required. Despite its insignificant nature, the negative relationship is consistent with the findings of the previous studies [3,25,72,73].

The results also show that distance to the city center has a significant negative effect on the PTE and TE of the airports. Thus, the reasonably close airports to the city center enable accessibility and leads to more airport traffic, generating more revenues from the flight and air travelers' movements. Furthermore, as expected, the population and age variables positively and significantly impact the TE and SE. Hence, a larger population may generate more airport demand and increase scale efficiency.

Finally, the regression result indicates that TGDSA's collaboration with private companies on airport operations has a positive but insignificant impact on efficiency. This finding is partially in line with the findings of previous studies [33,64,73–75]. However, on the contrary, [30] reports that the state-owned airports in Poland are more efficient. That is, there are controversial outcomes in the literature.

5. Conclusions and discussions

Airports play a vital role in economic growth and international trade by their high traffic volume and rapid growth potential. Hence, they are expected to provide efficient operations and high-quality services to passengers, airline companies, and other customers. Therefore, policymakers in the aviation industry should enhance the efficiency of airports.

The present study examined the efficiency of 46 targeted airports in Turkey from 2015 through 2018 via two methods; the spherical fuzzy AHP hybridized with the output-oriented DEA model and the Tobit panel regression model. We employed the DEA analysis in the first stage to estimate the efficiency of the airports, while the Tobit panel regression model was used in the second stage to identify the impact of explanatory variables on airport efficiency.

In the first stage, the experts' perceptions regarding the evaluation factors were included in the analysis process to produce solid results. Due to the selection process's high subjectivity, SFS-AHP was employed to elaborate the input and output factors. The results indicate a majority of the airports operate inefficiently. Most of the Turkish airports operate under IRS, implying that rising traffic volume would decrease unit costs, increasing efficiency. However, the operational scale of many airports is inefficiently small and has room for further improvement. These results align with the findings of prior studies [28,32,40]. Thus, underutilized airports should be enhanced to play a more significant role in air transport. In this respect, airport operators should use their own ability to utilize internal resources more efficiently than external business opportunities. The TGDSA could seek opportunities to increase scale efficiency to reach this goal. Obviously, airport managers may not easily manipulate air traffic in the short term. Thus, the visible results can be obtained only in the long term.

The results of the second-stage analysis via Tobit regression model identified two significant factors, i.e., number of tourists and distance to the city center, in explaining variations in PTE and TE of the airports, while the population and age have a positive and significant impact on the TE and SE. These results suggest that airports located in high-density touristic areas are expected to achieve higher efficiency scores. Further, the reasonably close airports to the city center enable accessibility and lead to more airport traffic. The results are in line with the prior studies [30,70,71].

5.1. Implications of the study

The results provide valuable insights for airport authorities and managers. The outcome of SFS-AHP is mainly in line with the previous studies, where the number of passengers, total revenues, and cargo volume were also highlighted as outputs [19,26,28,39], and terminal capacity, runway capacity, and total expenditures were also selected [62–65]. The novelty of our approach was to capture the inherent subjectivity of the input and output selection procedure with spherical fuzzy numbers, which was rarely addressed in the extant literature [32,76].

Central and local authorities should allocate the necessary resources to inefficient airports to improve their performance and increase their contributions to the regional economy. Airport authorities should also recognize the significant roles of Low-Cost Carriers on the growth of local airports, as argued by [77,78]. They should attract more airlines to offer air connectivity to travelers, particularly in smaller regions to stimulate tourism activity, investment opportunities, and the well-being of local communities. This argument is especially of vital importance for cities in the southern and northern Anatolia, such as Kars, Erzurum, Diyarbakır, Elazığ, Şanlı urfa, Trabzon, and Van. These cities stand out with their relatively high population and/or the growing economic activities. Increasing tourism potential in these cities is another factor that pushes up the efficiencies of the airports, as stated in [28].

Additionally, if airline companies have better knowledge of efficient airports, they could make informed decisions in selecting and cooperating with more efficient ones, as claimed by [19,76]. Airport operators may also use the results to understand better their own operating efficiency and the aspects that need further improvement [65,73]. Airport operators in the lower range of efficiency may also consider collaborating with the peer airports to increase operational efficiency as suggested by [79].

Policymakers should focus on new forms of partnerships, such as public–private-partnership that may increase the efficiency of Turkish airports. In addition, the privatization of more government-owned airports may provide a solid ground for a careful evaluation and restructuring of the inefficient airports. The same implications were also highlighted in previous studies [3,19,46,75], confirming the vital role of the private sector's efficiency-oriented operational approach. A higher private involvement may be an option to remedy inefficiencies related to Turkish airports' recent capacity expansions. Primarily, significant endeavors have been undertaken on infrastructure in 2011 [25]. Thus, we notice good investment opportunities for the private sector in semi-regional airports that have reached a sufficient scale and have increasing air traffic. However, a controversial finding was reported by [17] in the literature. The authors state that most of the Greek airports on the recent privatization list were already the most efficient ones that could attract capital from private investors. That is, the efficiency differences between public- and private-owned airports may not be a result of privatization, but the private sector is chasing the efficient and lucrative ones [17]. Another interesting issue is jointly owned airports, which was not studied in the current research. Some findings in the literature suggest that such an ownership structure may lead to inefficiency [62,75].

According to our results, a major portion of the airports in Turkey works under IRS condition, which is related to the enormous one-time investments that may not be matched with adequate demand. The findings of [3] support the same argument. Overinvestment in some regional airports in Turkey is another issue, which was also questioned in [67] for Japanese airports. However, we note that the large investments in the transportations infrastructure need a long time to become feasible by reaching a sufficient capacity utilization [40,67]. Therefore, the evaluation of long-term trends by taking this argument into account may be the subject of another study. Furthermore, the potential impacts of small airports as drivers of economic growth and regional development must also be considered while evaluating the feasibility of such investments [80].

Lastly, tourism plays a significant role in the efficiency scores of airports [71,80]. More direct flights from abroad to specific tourist destinations, such as Denizli, Nevşehir, and Hatay, would be beneficial [28]. An efficiency study on Spanish airports, a competing touristic destination with a similar tourism market as Turkey, provides additional insights on the role of tourism on the operational performance of airports [71]. The airports in high-density touristic areas share two common features: international tourism and seasonal air traffic. That is, the airports serving such regions are expected to be more efficient. This is also confirmed for Antalya, a high-density touristic destination. Interestingly, Muğla Dalaman (0.487 av. score) and Muğla Milas Bodrum (0.213 av. score), which two popular airports used on seasonal basis, do not support this statement. Apparently, the seasonality could be one factor of this result, which may be the focal point of further studies on Turkish airports. Obviously, air transport and tourism are highly interrelated. Thus, the policies regulating air transport must consider the potential effects on tourism [71].

5.2. Limitations of the study

Some limitations can also be addressed regarding this study. The selected input and output variables are partially determined based on the data availability. Obviously, the social and environmental impacts of the airports need to be investigated to evaluate their long-term performance. Another interesting research attempt may be a comparative study that benchmarks major Turkish airports with their global competitors. Future work may also explore the impact of other explanatory variables, such as business potential, hub status of airports, the number of connecting flights on the operational efficiency of the airports.

CRediT authorship contribution statement

Mustafa K. Yilmaz: Supervision, Conceptualization, Methodology, Data curation, Writing – original draft, Writing – reviewing and editing. **Ali Osman Kusakci:** Methodology, Conceptualization, Data curation, Writing – original draft, Formal analysis, Software, Visualization, Writing – review & editing. **Mine Aksoy:** Writing – original draft, Formal analysis, Validation. **Umit Hacioglu:** Validation, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

See Tables A.1 and A.2

Table A.1
The efficiency scores of the selected airports under variable return to scale assumption.

DMU	2015	2016	2017	2018	Average
Adana, ADA	1	1	1	1	1
Adı yaman, ADF	0.551	0.116	0.115	0.141	0.231
Ağrı Ahmed-i Hani, AJI	1	0.092	0.105	0.132	0.332
Amasya Merzifon, MZH	1	1	1	1	1
Ankara Esenboğa, ESB	0.501	0.407	0.459	0.545	0.478
Antalya, AYT	0.743	0.784	0.872	0.984	0.846
Balı kesir Kocaseyit, BZI	0.112	0.12	0.131	0.17	0.133
Batman, BAL	0.131	0.304	0.317	0.437	0.297
Bingöl, BGG	0.314	0.585	0.806	0.935	0.66
Bursa Yenişehir, BTZ	0.067	0.099	0.082	0.09	0.085
Çanakkale, GKD	1	0.196	0.189	0.19	0.394
Denizli Çardak, DNZ	0.172	0.186	0.221	0.245	0.206
Diyarbakır, DIY	0.855	0.244	0.196	0.265	0.39
Elazığ, EZS	0.45	0.447	0.423	0.454	0.444
Erzincan, ERC	0.102	0.12	0.134	0.179	0.134
Erzurum, ERZ	0.276	0.317	0.348	0.371	0.328
Gaziantep, GZT	0.522	0.484	0.563	0.583	0.538
Hakkari Yük.ova Selahaddin Eyyubi, YKO	1	0.053	0.114	0.15	0.329
Hatay, HTY	0.252	0.248	0.267	0.328	0.274
Iğdır Şehit Bülent Aydın, IGD	0.93	0.698	0.612	0.712	0.738
Isparta Süleyman Demirel, ISE	0.371	0.184	0.141	0.136	0.208
Istanbul Atatürk, ISL	1	1	1	1	1
Istanbul Sabiha Gökçen, SAW	1	1	1	1	1
Izmir Adnan Menderes, ADB	0.443	0.467	0.409	0.39	0.427
Kahramanmaraş, KCM	1	1	1	1	1
Kapadokya, NAV	0.374	0.376	0.131	0.297	0.295
Kars Harakani, KSY	0.337	0.192	0.201	0.184	0.229
Kastamonu, KFS	0.097	0.221	0.35	0.275	0.236
Kayseri, ASR	0.675	0.673	0.687	0.774	0.702
Kocaeli Cengiz Topel, KCO	0.479	0.393	0.188	0.221	0.32
Konya, KYA	0.287	0.288	0.285	0.311	0.293
Malatya, MLX	0.495	0.547	0.539	0.6	0.545
Mardin, MQM	0.195	0.222	0.223	0.246	0.222
Milas Bodrum, BJV	0.172	0.232	0.22	0.227	0.213
Muğla Dalaman, DLM	0.471	0.495	0.475	0.505	0.487
Muş, MSR	0.976	1	1	1	0.994
Ordu-Giresun, OGU	0.64	0.394	0.392	0.444	0.468
Samsun Çarşamba, SZF	0.662	0.671	0.407	0.622	0.591
Şanlı urfa Gap, GNY	0.26	0.286	0.291	0.307	0.286
Sinop, NOP	1	1	1	1	1
Şı rnak Şerafettin Elçi, NKT	0.731	0.387	0.429	0.492	0.51
Sivas Nuri Demirağ, VAS	0.236	0.252	0.224	0.268	0.245
Tekirdağ Çorlu, TEQ	0.204	0.168	0.104	0.095	0.143
Trabzon, TZX	0.583	0.663	0.735	0.705	0.672
Uşak, USQ	1	1	*	1	1
Van Ferit Melen, VAN	0.671	0.603	0.626	0.618	0.63
Mean	**0.551**	**0.461**	**0.457**	**0.492**	**0.49**

* Operation was temporarily seized.

Table A.2
The efficiency scores of the airports under variable return to scale assumption without outliers.

DMU	2015	2016	2017	2018	Average
Adana, ADA	1	1	1	1	1
Adı yaman, ADF	0.552	0.221	0.229	0.246	0.312
Ağrı Ahmed-i Hani, AJI	1	0.152	0.195	0.22	0.391
Amasya Merzifon, MZH	1	1	1	1	1
Balı kesir Kocaseyit, BZI	0.153	0.183	0.23	0.256	0.205
Batman, BAL	0.23	0.489	0.555	0.655	0.482
Bingöl, BGG	0.466	0.595	0.821	0.948	0.707
Bursa Yenişehir	0.072	0.118	0.109	0.111	0.102
Çanakkale, GKD	1	0.281	0.258	0.239	0.444
Denizli Çardak, DNZ	0.246	0.313	0.418	0.431	0.352
Diyarbakır, DIY	0.855	0.456	0.394	0.455	0.54
Elazığ, EZS	0.497	0.544	0.581	0.547	0.542
Erzincan, ERC	0.127	0.169	0.22	0.255	0.192
Erzurum, ERZ	0.281	0.339	0.393	0.402	0.353
Gaziantep, GZT	0.522	0.486	0.578	0.6	0.546
Hakkari Yük.ova Selahaddin Eyyubi, YKO	1	0.084	0.144	0.166	0.348
Hatay, HTY	0.343	0.329	0.424	0.515	0.402
Iğdır Şehit Bülent Aydın, IGD	0.93	0.698	0.615	0.712	0.738
Isparta Süleyman Demirel, ISE	0.462	0.366	0.276	0.269	0.343

(*continued on next page*)

Table A.2 (*continued*).

DMU	2015	2016	2017	2018	Average
Kahramanmaraş, KCM	1	1	1	1	1
Kapadokya, NAV	0.374	0.398	0.215	0.297	0.321
Kars Harakani, KSY	0.337	0.309	0.369	0.261	0.319
Kastamonu, KFS	0.123	0.223	0.485	0.329	0.29
Kayseri, ASR	0.759	0.824	0.953	1	0.884
Kocaeli Cengiz Topel, KCO	0.479	0.575	0.273	0.248	0.393
Konya, KYA	0.349	0.375	0.416	0.408	0.387
Malatya, MLX	0.495	0.577	0.593	0.632	0.574
Mardin, MQM	0.277	0.377	0.419	0.401	0.368
Milas Bodrum, BJV	0.839	1	1	1	0.959
Muğla Dalaman, DLM	1	1	1	1	1
Muş, MSR	0.976	1	1	1	0.994
Ordu-Giresun, OGU	1	0.77	0.677	0.714	0.79
Samsun Çarşamba, SZF	0.683	0.747	0.501	0.679	0.652
Şanlı urfa Gap, GNY	0.264	0.312	0.339	0.333	0.312
Sinop, NOP	1	1	1	1	1
Şı rnak Şerafettin Elçi, NKT	0.731	0.403	0.458	0.492	0.521
Sivas Nuri Demirağ, VAS	0.281	0.351	0.365	0.374	0.342
Tekirdağ Çorlu, TEQ	0.434	0.285	0.219	0.853	0.447
Trabzon, TZX	0.729	0.808	0.931	0.839	0.826
Uşak, USQ	1	1	*	1	1
Van Ferit Melen, VAN	0.671	0.659	0.702	0.67	0.675
Mean	**0.598**	**0.532**	**0.545**	**0.575**	**0.563**

* Operation was temporarily seized.

References

[1] A. Graham, Managing Airports:An International Perspective, fifth ed., Routledge, Routledge, Abingdon, Oxon; New York, 2018, http://dx.doi.org/10.4324/9781315269047, 2018.

[2] M.K. Akyüz, H. Kafalı, Ö. Altuntaş, An analysis on energy performance indicator and GWP at airports; a case study, Energy Sources A 43 (2021) 2402–2418, http://dx.doi.org/10.1080/15567036.2020.1761483.

[3] T. Ülkü, A comparative efficiency analysis of Spanish and Turkish airports, J. Air Transp. Manag. 46 (2015) 56–68, http://dx.doi.org/10.1016/j.jairtraman.2015.03.014.

[4] Turkish General Directorate of State Airports, Annual Reports, Ankara, 2019.

[5] H. Dinçer, Ü. Hacıoğlu, S. Yüksel, Balanced scorecard based performance measurement of European airlines using a hybrid multicriteria decision making approach under the fuzzy environment, J. Air Transp. Manage. 63 (2017) 17–33, http://dx.doi.org/10.1016/j.jairtraman.2017.05.005.

[6] S.-J. Hong, M. Jeon, The technical efficiency of French regional airports and low-cost carrier terminals, Sustainability 11 (2019) 5107, http://dx.doi.org/10.3390/su11185107.

[7] M. Noruzoliaee, B. Zou, Airfield infrastructure management using network-level optimization and stochastic duration modeling, Infrastructures 4 (2019) 2, http://dx.doi.org/10.3390/infrastructures4010002.

[8] Á. Rodríguez-Sanz, F. Gómez Comendador, R. Arnaldo Valdés, J. Cordero García, M. Bagamanova, Uncertainty management at the airport transit view, Aerospace 5 (2018) 59, http://dx.doi.org/10.3390/aerospace5020059.

[9] Z. Turskis, J. Antuchevičiene, V. Keršuliene, G. Gaidukas, Hybrid group MCDM model to select the most effective alternative of the second runway of the airport, Symmetry (Basel) 11 (2019) 792, http://dx.doi.org/10.3390/sym11060792.

[10] D. Wei, C. Liu, Fuzzy model and optimization for airport gate assignment problem, in: 2009 IEEE Int. Conf. Intell. Comput. Intell. Syst., IEEE, 2009, pp. 828–832.

[11] E. Zu, S.-Y. Liu, B.-M. Hsu, Y.-C. Wang, E.M. Lau, An analysis of the success factors for passenger boarding enthusiasm for low-cost regional airline routes, Sustainability 12 (2020) 6600.

[12] C. Zuniga, G. Boosten, A practical approach to monitor capacity under the CDM approach, Aerospace 7 (2020) 101, http://dx.doi.org/10.3390/aerospace7070101.

[13] D.C. Ferreira, R.C. Marques, M.I. Pedro, Comparing efficiency of holding business model and individual management model of airports, J. Air Transp. Manag. 57 (2016) 168–183.

[14] V. Liebert, H.-M. Niemeier, A survey of empirical research on the productivity and efficiency measurement of airports, J. Transp. Econ. Policy. 47 (2013) 157–189.

[15] D. Parker, The performance of BAA before and after privatisation: A DEA study, J. Transp. Econ. Policy. (1999) 133–145.

[16] E. Pels, P. Nijkamp, P. Rietveld, Inefficiencies and scale economies of European airport operations, Transp. Res. E 39 (2003) 341–361.

[17] A. Fragoudaki, D. Giokas, Airport efficiency in the dawn of privatization: The case of Greece, J. Air Transp. Manage. 86 (2020) 101821, http://dx.doi.org/10.1016/j.jairtraman.2020.101821.

[18] T. Ngo, K.W.H. Tsui, A data-driven approach for estimating airport efficiency under endogeneity: An application to New Zealand airports, Res. Transp. Bus. Manage. 34 (2020) 100412, http://dx.doi.org/10.1016/j.rtbm.2019.100412.

[19] F. Carlucci, A. Cirà, P. Coccorese, Measuring and explaining airport efficiency and sustainability: Evidence from Italy, Sustainability 10 (2018) 400, http://dx.doi.org/10.3390/su10020400.

[20] Y.-C. Chang, M.-M. Yu, P.-C. Chen, Evaluating the performance of Chinese airports, J. Air Transp. Manage. 31 (2013) 19–21, http://dx.doi.org/10.1016/j.jairtraman.2012.11.002.

[21] Y. Yoshida, H. Fujimoto, Japanese-airport benchmarking with the DEA and endogenous-weight TFP methods: testing the criticism of overinvestment in Japanese regional airports, Transp. Res. E 40 (2004) 533–546, http://dx.doi.org/10.1016/j.tre.2004.08.003.

[22] M.K. Yilmaz, A.O. Kusakci, E. Tatoglu, O. Icten, F. Yetgin, Performance evaluation of real estate investment trusts using a hybridized interval type-2 fuzzy AHP-DEA approach: The case of Borsa Istanbul, 2019, http://dx.doi.org/10.1142/S0219622019500354.

[23] H. Koçak, Efficiency examination of Turkish airports with DEA approach, Int. Bus. Res. 4 (2011) 204.

[24] J.C. Martín, C. Román, A benchmarking analysis of Spanish commercial airports, A comparison between SMOP and DEA ranking methods, Netw. Spat. Econ. 6 (2006) 111–134, http://dx.doi.org/10.1007/s11067-006-7696-1.

[25] H.H. Örkcü, C. Balıkçı, M.I. Dogan, A. Genç, An evaluation of the operational efficiency of turkish airports using data envelopment analysis and the Malmquist productivity index: 2009–2014 case, Transp. Policy 48 (2016) 92–104, http://dx.doi.org/10.1016/j.tranpol.2016.02.008.

[26] T. Tsekeris, Greek airports: Efficiency measurement and analysis of determinants, J. Air Transp. Manage. 17 (2011) 140–142, http://dx.doi.org/10.1016/j.jairtraman.2010.06.002.

[27] B. Ashuri, J. Wang, M. Shahandashti, M. Baek, A data envelopment analysis (DEA) model for building energy benchmarking, J. Eng. Des. Technol. (2019).

[28] V.S. Özsoy, H.H. Örkcü, Structural and operational management of Turkish airports: a bootstrap data envelopment analysis of efficiency, Util. Policy 69 (2021) 101180, http://dx.doi.org/10.1016/j.jup.2021.101180.

[29] T. Kohonen, Essentials of the self-organizing map, Neural Netw. 37 (2013) 52–65.

[30] A.E. Ripoll-Zarraga, S. Huderek-Glapska, Airports' managerial human capital, ownership, and efficiency, J. Air Transp. Manag. 92 (2021) 102035, http://dx.doi.org/10.1016/j.jairtraman.2021.102035.

[31] X.L. Fernández, J. Gundelfinger, P. Coto-Millán, The impact of logistics and intermodality on airport efficiency, Transp. Policy. (2021) http://dx.doi.org/10.1016/j.tranpol.2021.05.008.

[32] S. Güner, H.İ. Cebeci, J.J.M. Antunes, P.F. Wanke, Sustainable efficiency drivers in eurasian airports: Fuzzy NDEA approach based on Shannon's entropy, J. Air Transp. Manage. 92 (2021) 102039, http://dx.doi.org/10.1016/j.jairtraman.2021.102039.

[33] T.M. Huynh, G. Kim, H.-K. Ha, Comparative analysis of efficiency for major Southeast Asia airports: A two-stage approach, J. Air Transp. Manage. 89 (2020) 101898, http://dx.doi.org/10.1016/j.jairtraman.2020.101898.
[34] M.F. Bongo, L.A. Ocampo, A hybrid fuzzy MCDM approach for mitigating airport congestion: A case in Ninoy Aquino International Airport, J. Air Transp. Manage. 63 (2017) 1–16, http://dx.doi.org/10.1016/j.jairtraman.2017.05.004.
[35] Z. Wang, W.-K. Song, Sustainable airport development with performance evaluation forecasts: A case study of 12 Asian airports, J. Air Transp. Manage. 89 (2020) 101925, http://dx.doi.org/10.1016/j.jairtraman.2020.101925.
[36] R.R. Martıń-Cejas, An approximation to the productive efficiency of the Spanish airports network through a deterministic cost frontier, J. Air Transp. Manage. 8 (2002) 233–238, http://dx.doi.org/10.1016/S0969-6997(01)00056-4.
[37] E. Fernandes, R.R. Pacheco, Efficient use of airport capacity, Transp. Res. A 36 (2002) 225–238, http://dx.doi.org/10.1016/S0965-8564(00)00046-X.
[38] L.W. Fan, F. Wu, P. Zhou, Efficiency measurement of Chinese airports with flight delays by directional distance function, J. Air Transp. Manage. 34 (2014) 140–145, http://dx.doi.org/10.1016/j.jairtraman.2013.10.002.
[39] P. Lai, A. Potter, M. Beynon, A. Beresford, Evaluating the efficiency performance of airports using an integrated AHP/DEA-AR technique, Transp. Policy 42 (2015) 75–85, http://dx.doi.org/10.1016/j.tranpol.2015.04.008.
[40] D. Ennen, I. Batool, Airport efficiency in Pakistan - A data envelopment analysis with weight restrictions, J. Air Transp. Manage. 69 (2018) 205–212, http://dx.doi.org/10.1016/j.jairtraman.2018.02.007.
[41] O.D. Olariaga, L.P. Moreno, Measurement of airport efficiency, The case of Colombia, Transp. Telecommun. 20 (2019) 40–51.
[42] E. Stichhauerova, N. Pelloneova, An efficiency assessment of selected German Airports using the DEA model, J. Compet. 11 (2019) 135–151, http://dx.doi.org/10.7441/joc.2019.01.09.
[43] R.D. Banker, A. Charnes, W.W. Cooper, Some models for estimating technical and scale inefficiencies in data envelopment analysis, Manage. Sci. 30 (1984) 1078–1092, http://dx.doi.org/10.1287/mnsc.30.9.1078.
[44] D. Liu, Measuring aeronautical service efficiency and commercial service efficiency of East Asia airport companies: An application of network data envelopment analysis, J. Air Transp. Manage. 52 (2016) 11–22, http://dx.doi.org/10.1016/j.jairtraman.2015.12.001.
[45] A.C. Pacagnella, P.S. Hollaender, G.V. Mazzanati, W.W. Bortoletto, Efficiency drivers of international airports: A worldwide benchmarking study, J. Air Transp. Manage. 90 (2021) 101960, http://dx.doi.org/10.1016/j.jairtraman.2020.101960.
[46] B. Keskin, C.D. Köksal, A hybrid AHP/DEA-AR model for measuring and comparing the efficiency of airports, Int. J. Prod. Perform. Manage. 68 (2019) 524–541, http://dx.doi.org/10.1108/IJPPM-02-2018-0043.
[47] R.A. Villano, C.-D.T.T. Tran, Performance of private higher education institutions in Vietnam: evidence using DEA-based bootstrap directional distance approach with quasi-fixed inputs, Appl. Econ. 50 (2018) 5966–5978.
[48] N.A. Tran, G. Shively, P. Preckel, A new method for detecting outliers in Data Envelopment Analysis, Appl. Econ. Lett. 17 (2010) 313–316.
[49] U. Maulik, S. Bandyopadhyay, Performance evaluation of some clustering algorithms and validity indices, IEEE Trans. Pattern Anal. Mach. Intell. 24 (2002) 1650–1654, http://dx.doi.org/10.1109/TPAMI.2002.1114856.
[50] J.C. Dunn, A fuzzy relative of the ISODATA process and its use in detecting compact well-separated clusters, J. Cybern. 3 (1973) 32–57, http://dx.doi.org/10.1080/01969727308546046.
[51] T. Coelli, A guide to DEAP version 2.1: a data envelopment analysis (computer) program, Cent. Effic. Product. Anal. Univ. New Engl. Aust. 96 (1996) 1–49.
[52] A. Görener, B. Ayvaz, A.O. Kuşakcı, E. Altınok, A hybrid type-2 fuzzy based supplier performance evaluation methodology: The Turkish Airlines technic case, Appl. Soft Comput. 56 (2017) 436–445, http://dx.doi.org/10.1016/j.asoc.2017.03.026.
[53] F.K. Gündoğdu, C. Kahraman, Spherical fuzzy analytic hierarchy process (AHP) and its application to industrial robot selection, in: Int. Conf. Intell. Fuzzy Syst, Springer, 2019, pp. 988–996.
[54] F. Kutlu Gündoğdu, C. Kahraman, Spherical fuzzy sets and spherical fuzzy TOPSIS method, J. Intell. Fuzzy Syst. 36 (2019) 337–352.
[55] A. Charnes, W.W. Cooper, E. Rhodes, Measuring the efficiency of decision making units, European J. Oper. Res. 2 (1978) 429–444, http://dx.doi.org/10.1016/0377-2217(78)90138-8.
[56] T. Kohonen, Self-organized formation of topologically correct feature maps, Biol. Cybernet. 43 (1982) 59–69.
[57] K. Ito, I. Couckuyt, R. D'Ippolito, T. Dhaene, Design space exploration using Self-Organizing Map based adaptive sampling, Appl. Soft Comput. 43 (2016) 337–346, http://dx.doi.org/10.1016/j.asoc.2016.02.036.
[58] A.T. Azar, S.A. El-Said, A.E. Hassanien, Fuzzy and hard clustering analysis for thyroid disease, Comput. Methods Programs Biomed. 111 (2013) 1–16.
[59] K. Kumar, Self-organizing map (SOM) neural networks for air space sectoring, in: 2014 Int. Conf. Comput. Intell. Commun. Networks, IEEE, 2014, pp. 1096–1100, http://dx.doi.org/10.1109/CICN.2014.230.
[60] J. Chen, J. Chen, X. Zhang, Reliability prediction model of aircraft using self-organizing map, in: 2007 IEEE Int. Conf. Autom. Logist, IEEE, 2007, pp. 680–683, http://dx.doi.org/10.1109/ICAL.2007.4338650.
[61] J. Zhao, X. Chen, An intelligent evaluation method to analyze the competitiveness of airlines, Math. Probl. Eng. 2020 (2020) 1–9, http://dx.doi.org/10.1155/2020/8589346.
[62] M. Abbott, Reform and efficiency of New Zealand's airports, Util. Policy 36 (2015) 1–9, http://dx.doi.org/10.1016/j.jup.2015.05.001.
[63] C.P. Barros, Technical change and productivity growth in airports: A case study, Transp. Res. A 42 (2008) 818–832, http://dx.doi.org/10.1016/j.tra.2008.01.029.
[64] T.H. Oum, N. Adler, C. Yu, Privatization, corporatization, ownership forms and their effects on the performance of the world's major airports, J. Air Transp. Manage. 12 (2006) 109–121, http://dx.doi.org/10.1016/j.jairtraman.2005.11.003.
[65] W.H.K. Tsui, A. Gilbey, H.O. Balli, Estimating airport efficiency of New Zealand airports, J. Air Transp. Manage. 35 (2014) 78–86, http://dx.doi.org/10.1016/j.jairtraman.2013.11.011.
[66] R. Robert Russell, Measures of technical efficiency, J. Econ. Theory 35 (1985) 109–126, http://dx.doi.org/10.1016/0022-0531(85)90064-X.
[67] H.-K. Ha, Y. Yoshida, A. Zhang, Comparative analysis of efficiency for major Northeast Asia airports, Transp. J. 49 (2010) 9–23.
[68] S. Ercan, G. Kayakutlu, Scheduling in energy systems, Sigma J. Eng. Nat. Sci. Fen Bilim. Derg. 33 (2015).
[69] A. Hoff, Second stage DEA: Comparison of approaches for modelling the DEA score, European J. Oper. Res. 181 (2007) 425–435, http://dx.doi.org/10.1016/j.ejor.2006.05.019.
[70] D. Albalate, G. Bel, Tourism and urban public transport: Holding demand pressure under supply constraints, Tour. Manage. 31 (2010) 425–433, http://dx.doi.org/10.1016/j.tourman.2009.04.011.
[71] X.L. Fernández, P. Coto-Millán, B. Díaz-Medina, The impact of tourism on airport efficiency: The Spanish case, Util. Policy 55 (2018) 52–58, http://dx.doi.org/10.1016/j.jup.2018.09.002.
[72] S. Pathosmiri, A. Haghani, M. Dresner, R.J. Windle, Assessment of airports performance with joint consideration of desirable and undesirable outputs, in: 10th Annu. World Conf. Air Transp. Res. Soc. Proc. (CD-ROM), Nagoya, Japan, 2006.
[73] W.H. Kan Tsui, H.O. Balli, A. Gilbey, H. Gow, Operational efficiency of Asia–Pacific airports, J. Air Transp. Manage. 40 (2014) 16–24, http://dx.doi.org/10.1016/j.jairtraman.2014.05.003.
[74] C. Pestana Barros, P.U.C. Dieke, Performance evaluation of Italian airports: A data envelopment analysis, J. Air Transp. Manage. 13 (2007) 184–191, http://dx.doi.org/10.1016/j.jairtraman.2007.03.001.
[75] T.H. Oum, J. Yan, C. Yu, Ownership forms matter for airport efficiency: A stochastic frontier investigation of worldwide airports, J. Urban Econ. 64 (2008) 422–435, http://dx.doi.org/10.1016/j.jue.2008.03.001.
[76] W. Lu, S.H. Park, T. Huang, G.T. Yeo, An analysis for Chinese airport efficiency using weighted variables and adopting CFPR, Asian J. Shipp. Logist. 35 (2019) 230–242, http://dx.doi.org/10.1016/j.ajsl.2019.12.010.
[77] I. Henke, M. Esposito, V. della Corte, G. del Gaudio, F. Pagliara, Airport efficiency analysis in Europe including user satisfaction: A non-parametric analysis with DEA approach, Sustainability 14 (2021) 283, http://dx.doi.org/10.3390/su14010283.
[78] V.D. Pyrialakou, M.G. Karlaftis, P.G. Michaelides, Assessing operational efficiency of airports with high levels of low-cost carrier traffic, J. Air Transp. Manage. 25 (2012) 33–36, http://dx.doi.org/10.1016/j.jairtraman.2012.05.005.
[79] Y. Jiang, F. Liao, Q. Xu, Z. Yang, Identification of technology spillover among airport alliance from the perspective of efficiency evaluation: The case of China, Transp. Policy 80 (2019) 49–58, http://dx.doi.org/10.1016/j.tranpol.2019.05.004.
[80] A.E. Ripoll-Zarraga, J.M. Raya, Tourism indicators and airports' technical efficiency, Ann. Tour. Res. 80 (2020) 102819, http://dx.doi.org/10.1016/j.annals.2019.102819.