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Analysis of the Operational Performance of International Aviation Institutions with the EIFTOPSIS Method

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ABSTRACT

Purpose: The main goal of this study is to rank the operational performance variables used in aviation according to their importance levels and to measure the operational performance of international aviation institutions.

***Methodology*:** An extended intuitionistic fuzzy TOPSIS method with maximum deviation is used in criterion weighting and performance measurement, which is relatively new and has no use case in aviation.

Findings: According to the results obtained in the study, it is understood that the total airport movements controlled among the variables used in the operational performance evaluation are the criterion with the highest importance. DSNA (France), ENAIRE (Spain), and DHMI (Türkiye) are in the top three in the best operational performance rankings.

Originality: The operational performance variables offered by EUROCONTROL have been tested for the first time with the extended intuitionistic fuzzy TOPSIS method.

Keywords*:* Aviation, Operational Performance, Intuitionistic Fuzzy Logic, EIFTOPSIS, MCDM.

JEL Codes: D81, L25, L93.

Uluslararası Havacılık Kurumlarının Operasyonel Performansının GSBTOPSIS Yöntemi ile Analizi

ÖZET

Amaç: Çalışmanın temel amacı havacılık alanında kullanılan operasyonel performans değişkenlerinin önem düzeylerine göre derecelendirilmesi ve uluslararası havacılık işletmelerinin operasyonel performanslarının ölçülmesidir.

***Yöntem*:** Kriter ağırlıklandırmada ve performans ölçümünde nispeten yeni ve havacılık alanında kullanım örneği bulunmayan maksimum sapma ile genişletilmiş sezgisel bulanık TOPSIS yöntemi kullanılmıştır.

Bulgular: Araştırma sonuçlarına göre operasyonel performans değerlendirmesinde kullanılan değişkenler içerisinde kontrol edilen toplam havaalanı hareketliliği en yüksek önem ağırlığına sahip kriter olduğu anlaşılmaktadır. En iyi operasyonel performans sıralamasında DSNA (Fransa), ENAIRE (İspanya) ve DHMİ (Türkiye) ilk üç sırada yer almaktadır.

Özgünlük: EUROCONTROL tarafından sunulan operasyonel performans değişkenleri ilk kez genişletilmiş sezgisel bulanık TOPSIS yöntemi ile test edilmiştir.

Anahtar Kelimeler*:* Havacılık, Operasyonel Performans, Sezgisel Bulanık Mantık, GSBTOPSIS, ÇKKV.

JEL Kodları: D81, L25, L93.

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1. INTRODUCTION

The aviation sector, which is a segment of the travel and transportation industry, has recently developed quite rapidly. The annual growth of the global aviation industry is 5-6%. The development of the aviation industry is due to the increase in international trade and the tendency of people to travel (Yu et al., 2008). The aviation industry plays an integral role in the creation of the macro-economy due to its effects on its own activities and other related industries (Belobaba, 2015:116). The aviation industry is part of general transport networks. In addition to having common features with other transportation systems, it also has its characteristics. With the use of specialized equipment due to technological development, the aviation industry is becoming more and more capital-intensive. Due to the fierce competitive pressure and high fixed costs in the industry, the survival and sustainability of aviation companies have become more difficult, especially during periods of low demand. The fierce competition in the aviation industry has become more evident today. Competitive conditions force organizations to reduce costs while increasing quality (Lu, 2012). To overcome these key challenges, to be successful and survive in the global airline market, performance measurement in aviation companies can be an important key (Wu and Liao, 2014).

The current conditions of the global economy and the size of airports in passenger and cargo traffic make performance evaluations an indispensable task (Shojaei et al., 2018). Barros and Dieke (2008) discuss the importance of performance evaluation of aviation enterprises for three main reasons:

- Efficient aviation services are essential for the sustainability of airline operations.
- Performance measurement studies are helpful in evaluating the effectiveness of governments' investments.
- Provides managers and decision-makers in aviation businesses with a source of information about benchmarks with other businesses.

For these reasons, performance evaluation with appropriate different approach tools is very important for the effective management of aviation services.

Due to the multitude of indices in performance evaluation methods, measuring values can be difficult and complex, and the presence of multiple variables also involves high uncertainty and blurriness (Anbanandam et al., 2011). Various models have been presented by researchers to examine performance in uncertain environments. To cope with the uncertainty in the aviation industry, the extended intuitionistic fuzzy TOPSIS (EIFTOPSIS) method, which is an Multi-Criteria Decision-Making (MCDM) approach and proposed as a new model by Shen et al, (2018), was used in this study. This new model, which eliminates the drawbacks of the existing intuitive fuzzy set distance measure, is used for the first time in performance measurement in the aviation industry. This newly developed method was preferred because it does not have any application in the aviation industry, it can help decision-makers in combating uncertainty, and it models a stronger distance measure by eliminating the weaknesses of existing distance measures.

This study, which focuses on the operational performance of international aviation service providers, basically consists of 4 sections. In the first section, the literature review and the conceptual framework of operational performance are explained. The methodology and algorithms used are presented in the next section. Then, analysis and findings are given. In the last section, research results and recommendations are mentioned.

2. OPERATIONAL PERFORMANCE

The global air transport industry is becoming more and more competitive. Airline companies have to make quick decisions in an intensely competitive environment to survive in the sector. While low input prices were important in the past to provide a competitive advantage, the strength of operational performance is more evident today (Wu and Liao, 2014). Operational performance is important for companies as it demonstrates the improvement in quality in terms of flexibility of service delivery (Zhang and Xia, 2013). Operational performance, which supports competitive advantage (Narasimhan and Das, 2001; Schroeder et al., 2011), continues to attract the attention of managers and industry observers from past to present.

In recent years, the issue of performance evaluation has created interest in every sector. In the performance evaluation literature, some studies evaluate the performance of organizations through both subjective and objective data (Ouellette et al., 2010; Lu et al., 2012, Gramani, 2012; Lee et al., 2013).

When the relevant literature is examined, performance measurement studies related to the aviation sector are encountered. In the studies conducted, Schefczyk (1993) compared the operational performance of 15 international airline companies in 1990 with the data envelopment analysis (DEA) method. Färe et al. (2007) analyzed the performance of an airline company with the Malmquist Efficiency Index, taking into account the time factor. Barbot et al., (2008) examined the effectiveness and efficiency of 49 international airline companies in a single period using DEA and total factor productivity approaches. He also investigated the differences in productivity of factors. Barros and Peypoch (2009) analyzed the performance of the members of the European Airlines Association between 2000 and 2005 using the DEA method by combining operational and financial variables. Assaf and Josiassen (2011) focused on UK airlines and measured their efficiency. They tried to explain the sources of efficiency differences using an innovative DEA model and a 5-year data set of 15 airline companies. Lu et al., (2012) examined the relationship between operational performance and corporate governance of 30 airline companies operating in the USA with the help of the two-stage DEA method. Zou and Hansen (2012) empirically investigated the operational performance of US airlines during the period 1995-2007 and its impact on cost structure using the aggregate statistical cost estimation approach. Wanke et al. (2015) evaluated the performance of Asian airlines in the 2006-2012 period with the MCDM method. Wanke and Barros (2016) investigated the operational performance of Latin American airlines in the 2010-2014 period using the virtual frontier dynamic DEA method. Yu et al. (2017) examined the dynamic production efficiency, service efficiency, and overall operational efficiency of 30 global airline companies from 2009 to 2012 with the two-stage dynamic network DEA method. Seufert et al. (2017) evaluated the operational performance of the world's largest airlines between 2007 and 2013. In the study, a production indicator is proposed for undesirable outputs in airline performance analysis. Mhlanga et al. (2018) examined the factors affecting the operational efficiency of airlines in South Africa and their impact on airline performance. Pineda et al. (2018) ranked airlines in the US based on their financial and operational performance. They proposed an integrated model combining data mining and MCDM by identifying critical factors for improving airline performance. Bakir et al. (2020) evaluated the operational performance of 11 airlines operating in emerging markets with a new proposed MCDM method. Kiraci and Yasar (2020) examined the operational data of 52 airlines, which control more than 90% of the global airline transportation industry, between 1990 and 2017 with panel data analysis. They report the factors determining the operational performance of airlines. Pinchemel et al. (2022) investigated the relationship between management and operational efficiency of the four largest private airlines in Brazil. The relationship between performance indicators was tried to be revealed by regression analysis using panel data from 2009 to 2017. Looking at the scientific literature, there is a consensus that operational performance is based on service delivery, quality practices, efficiency, and environmental and legal responsibility (Sharma and Modgil, 2020; Heizer et al., 2020:34). Performance measurements for all studies should be accessible, reliable, and accurate (Wyman, 2012).

The operation and management of airports are carried out by air transport service provider companies. The management of the airport is similar to other sectors in terms of corporate ethics and operational efficiency (Dožić, 2019). Researchers generally make use of operational or financial criteria when evaluating the overall performance of aviation enterprises (Gramani, 2012). In recent performance measurement studies, a transition from simple financial indicators to a multidimensional measurement perspective is observed. Therefore, researchers focus on multidimensional indicators (Lu et al., 2012). The operational efficiency of the airport operation can be examined in four dimensions these; airline companies, aviation management services, passengers, and airports. Airline companies cover the number of routes and the number of take-offs and landings. The aviation control service includes the number of aviation controllers. Passenger ratings include the total number of passengers served. The airport is evaluated in terms of workforce, terminal facilities, aviation facilities, traffic volume, and revenue. The overall operational performance is evaluated by examining the productivity of employees, aviation, passenger and airline service levels (Wang et al., 2004).

Managers, decision-makers, and people in organizations are faced with a wide variety of decisions in their daily lives that require evaluation related to multiple features, criteria, and factors (Bai et al., 2014). Improving operational performance in aviation businesses requires a decision-making process that includes a systematic approach due to its complex nature. Such decision-making processes require consideration of sometimes contradictory and sometimes interrelated criteria (Gomes et al., 2014). All these factors make performance evaluation in aviation companies a MCDM problem (Bae et al., 2021).

A review of the literature reveals that operational performance studies in the aviation sector are conducted on airline companies. However, the aviation industry is multidimensional. Airport operations and management play a key role in the aviation industry. It is noticed that airport businesses are ignored in operational performance measurement and there is a gap in the aviation sector literature. This research will contribute to the literature in this context with its originality.

3. METHOD

The fuzzy set (FS) theory proposed by Zadeh (1965) has been successfully applied in many fields to overcome uncertainty problems. The basis of the FS theory is based on the membership degrees of the set elements. Researchers have developed different applications for the traditional FS theory recently. Intuitive fuzzy set (IFS), developed by Atanassov (1986) and an extension of classical FS, is explained by membership degree, non-membership degree and hesitation degree. Many researchers state that the IFS approach offers meaningful results in dealing with blurriness and is very useful in applications (Shen et al., 2016).

MCDM methods help decision-makers organize and synthesize information in a way that gives them confidence in decision-making (Belton and Stewart, 2002:264). MCDM methods provide a systematic quantitative approach to decision problems involving multiple criteria and actions. MCDM can assist decision makers in rationally evaluating all the important objective and subjective criteria for a problem (Hatami-Marbini and Tavana, 2011). TOPSIS method, which is one of the MCDM approaches, offers managers the opportunity to make decisions based on solid foundations. TOPSIS was developed to minimize the distance of an object value from the positive ideal solution and maximize its distance from the negative ideal solution (Hwang and Yoon, 1981). TOPSIS method can be categorized as an objective, deterministic, discrete alternative, compensatory MCDM approach. TOPSIS method, which is one of the MCDM approaches that is used successfully in many fields and gives effective results, draws attention in research (Junior et al., 2014; Boutkhoum et al., 2018; Prascevic and Prascevic, 2017; Roy and Dutta, 2019; Samanlioglu et al., 2018; Venkatesh et al., 2019; Bai and Sarkis, 2013; Chen and Tzeng, 2004; Krohling and Campanharo, 2011; Wang and Chang, 2007).

In traditional TOPSIS methods, criteria have definite values in the evaluation of alternatives. Recently, the combination of the TOPSIS method and IFSs has received widespread attention from many researchers (Shen et al., 2018). In the literature, some studies use the Fuzzy TOPSIS approach to measure performance in the aviation industry (Wang, 2008; Garg, 2016; Barros and Wanke, 2015). However, the proposed TOPSIS methods in the heuristic fuzzy environment have some disadvantages, such as not being able to take an alternative order of preference and negative effects in the real decision-making process (Ye, 2010; Joshi and Kumar, 2014; Wang et al., 2016). In this study, the heuristic fuzzy distance measure, which was proposed by Shen et al. (2018) as a new approach, and which overcomes the drawbacks of the existing IFS distance measure, was used. The basic algorithm of the IFS approach is shown in Equations 1-3.

For any $x \in X$ where $A = \{(x, \mu A\ (x), \nu A\ (x))\ /x \in X\}$ for the intuitionistic fuzzy set A in the set X;

$$\mu A : X \to [0,1], x \in X \to = \mu A\ (x) \in [0,1] \tag{1}$$

the degree of membership of $x \in X$ to A

$$\nu A : X \to [0,1], x \in X \to = \nu A\ (x) \in [0,1] \tag{2}$$

the degree of non-membership of $x \in X$ to A, and

$$\mu A\ (x) + \nu A\ (x) \leq 1 \tag{3}$$

is expressed.

The degree of hesitation or uncertainty of X in A is calculated by the function $\pi A\ (x) = 1 - \mu A\ (x) - \nu A\ (x)$ (Atanassov, 1986). Especially if $\pi A\ (x) = 0, A$ is reduced to a fuzzy set.

In MCDM problems, decision-makers need to weigh more than one criterion according to the level of importance and choose the most appropriate one among various alternatives. Among the MCDM methods, the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method attracts a lot of attention. The extended intuitionistic fuzzy TOPSIS (EIFTOPSIS) approach based on the new distance measure is preferred to be used in this article because of its effective results and advantages. The application procedure and mathematical notations of the EIFTOPSIS method, which is integrated with the extended intuitionistic fuzzy approach, are presented below (Shen et al., 2018).

Step 1: A decision matrix containing row-based competitive alternatives (i) and column-based criteria (j) is created as shown in Equation 4.

$$D = (a_{ij})_{mxn} = \begin{matrix} \\ A_1 \\ A_2 \\ \vdots \\ A_i \end{matrix} \begin{matrix} \begin{matrix} C_1 & C_2 & \cdots & C_j \end{matrix} \\ \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1j} \\ a_{21} & a_{22} & \cdots & a_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ a_{i1} & a_{i2} & \cdots & a_{ij} \end{pmatrix} \end{matrix} \tag{4}$$

Step 2: Each value in the decision matrix is normalized with the help of Equation 5 (Jahanshahloo et al., 2006).

$$n_{ij} = x_{ij} / \sqrt{\sum_{j=1}^{m} x_{ij}^2} \qquad i = 1\ldots, m.\ j = 1, \ldots, n \tag{5}$$

Step 3: The exact data in the normalized decision matrix are transformed into intuitionistic fuzzy values by using the Equations 6-8 respectively (Atanassov, 1986; Singh et al., 2019).

$$v_i' = 1 - \mu_i \quad (6)$$

$$\pi_i = \frac{v_i'}{\sum_{i=1}^{n} v_i'} \quad (7)$$

$$v_i = 1 - \mu_i - \pi_i \quad (8)$$

Step 4: IFSs-based positive ideal solution values for each criterion are calculated using $\tilde{a}^+ = \tilde{a}_1^+, \tilde{a}_2^+, \dots, \tilde{a}_3^+$, and negative ideal solution values $\tilde{a}^- = \tilde{a}_1^-, \tilde{a}_2^-, \dots, \tilde{a}_3^-$ using Equations 9 and 10, respectively. C^+refers to the benefit cluster criteria and C^- refers to the cost cluster criteria in the equations.

$$\tilde{a}_j^+ = \begin{cases} \left(max_{1\le i\le m}\{\mu_{ij}\}, min_{1\le i\le m}\{v_{ij}\}\right) = \left(\mu_j^+, v_j^+\right), \ if\ C_j \in C^+ \\ \left(min_{1\le i\le m}\{\mu_{ij}\}, mak_{1\le i\le m}\{v_{ij}\}\right) = \left(\mu_j^+, v_j^+\right), \ if\ C_j \in C^- \end{cases} \quad (9)$$

$$\tilde{a}_j^- = \begin{cases} \left(min_{1\le i\le m}\{\mu_{ij}\}, mak_{1\le i\le m}\{v_{ij}\}\right) = \left(\mu_j^+, v_j^+\right), \ if\ C_j \in C^+ \\ \left(mak_{1\le i\le m}\{\mu_{ij}\}, min_{1\le i\le m}\{v_{ij}\}\right) = \left(\mu_j^+, v_j^+\right), \ if\ C_j \in C^- \end{cases} \quad (10)$$

Step 5: With the new distance measure shown in Equations 11-12, the intuitionistic fuzzy distances between $\tilde{a}_{ij}$, $\tilde{a}_j^-$ and $\tilde{a}_{ij}$, $\tilde{a}_j^+$ are calculated separately. Then, intuitionistic fuzzy distance matrices in Equations 13 and 14 are generated.

$$\tilde{\mu}_{ij} = \mu_{ij}(1 + \tfrac{2}{3}\pi_{ij}(1 + \pi_{ij})) \quad (11)$$

$$\tilde{v}_{ij} = v_{ij}(1 + \tfrac{2}{3}\pi_{ij}(1 + \pi_{ij})) \quad (12)$$

$$D^+ = (d(\tilde{a}_{ij}, \tilde{a}_j^+))_{mxn} = \begin{matrix} & C_1 & C_2 & \cdots & C_j \\ A_1 & d(\tilde{a}_{11}, \tilde{a}_1^+) & d(\tilde{a}_{12}, \tilde{a}_2^+) & \cdots & d(\tilde{a}_{1j}, \tilde{a}_j^+) \\ A_2 & d(\tilde{a}_{21}, \tilde{a}_1^+) & d(\tilde{a}_{22}, \tilde{a}_2^+) & \cdots & d(\tilde{a}_{2j}, \tilde{a}_j^+) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ A_i & d(\tilde{a}_{i1}, \tilde{a}_1^+) & d(\tilde{a}_{i2}, \tilde{a}_2^+) & \cdots & d(\tilde{a}_{ij}, \tilde{a}_j^+) \end{matrix} \quad (13)$$

$$D^- = (d(\tilde{a}_{ij}, \tilde{a}_j^-))_{mxn} = \begin{matrix} & C_1 & C_2 & \cdots & C_j \\ A_1 & d(\tilde{a}_{11}, \tilde{a}_1^-) & d(\tilde{a}_{12}, \tilde{a}_2^-) & \cdots & d(\tilde{a}_{1j}, \tilde{a}_j^-) \\ A_2 & d(\tilde{a}_{21}, \tilde{a}_1^-) & d(\tilde{a}_{22}, \tilde{a}_2^-) & \cdots & d(\tilde{a}_{2j}, \tilde{a}_j^-) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ A_i & d(\tilde{a}_{i1}, \tilde{a}_1^-) & d(\tilde{a}_{i2}, \tilde{a}_2^-) & \cdots & d(\tilde{a}_{ij}, \tilde{a}_j^-) \end{matrix} \quad (14)$$

Step 6: The Composite intuitionistic fuzzy distance matrix expressed by Equation 15 is created. In the best performance data, $d(\tilde{a}_{ij}, \tilde{a}_j^-)$ values should be large and $d(\tilde{a}_{ij}, \tilde{a}_j^+)$ values should be small. In other words, the data with the best performance should be far from the cost criteria and close to the benefit criteria. The larger the Z_{ij}^* value, the better the $\tilde{a}_{ij}$ performance data indicates.

$$D^* = (Z_{ij}^*)_{mxn} = \begin{matrix} & C_1 & C_2 & \cdots & C_j \\ A_1 & d(\tilde{a}_{11}, \tilde{a}_1^-) - d(\tilde{a}_{11}, \tilde{a}_1^+) & d(\tilde{a}_{12}, \tilde{a}_2^-) - d(\tilde{a}_{12}, \tilde{a}_2^+) & \cdots & d(\tilde{a}_{1j}, \tilde{a}_j^-) - d(\tilde{a}_{1j}, \tilde{a}_j^+) \\ A_2 & d(\tilde{a}_{21}, \tilde{a}_1^-) - d(\tilde{a}_{21}, \tilde{a}_1^+) & d(\tilde{a}_{22}, \tilde{a}_2^-) - d(\tilde{a}_{22}, \tilde{a}_2^+) & \cdots & d(\tilde{a}_{2j}, \tilde{a}_j^-) - d(\tilde{a}_{2j}, \tilde{a}_j^+) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ A_i & d(\tilde{a}_{i1}, \tilde{a}_1^-) - d(\tilde{a}_{i1}, \tilde{a}_1^+) & d(\tilde{a}_{i2}, \tilde{a}_2^-) - d(\tilde{a}_{i2}, \tilde{a}_2^+) & \cdots & d(\tilde{a}_{ij}, \tilde{a}_j^-) - d(\tilde{a}_{ij}, \tilde{a}_j^+) \end{matrix}$$

$$= \begin{matrix} & C_1 & C_2 & \cdots & C_j \\ A_1 & Z_{11}^* & Z_{12}^* & \cdots & Z_{1j}^* \\ A_2 & Z_{21}^* & Z_{22}^* & \cdots & Z_{2j}^* \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ Z_{11}^* & a_{i1} & Z_{i2}^* & \cdots & Z_{ij}^* \end{matrix} \quad (15)$$

Step 7: $w_{ij}^{*}(j = 1,2,\ldots,n)$ importance weights are calculated for each criterion. The maximum deviation method shown in Equation 16 can be used to determine the weight of each of the criteria. In this method, decision makers derive the weights of the criteria from the variability of the data. w_j^{*} shows the optimal weight for each criterion.

$$w_j^{*} = \frac{\sum_{i=1}^{m} \sum_{k=1}^{m} |z_{ij} - z_{kj}|}{\sum_{i=1}^{n} \sum_{i=1}^{m} \sum_{k=1}^{m} |z_{ij} - z_{kj}|} \qquad (16)$$

Step 8: The weighted intuitionistic fuzzy distance measures of each alternative are calculated with the help of Equation 17. At the last stage in the application procedure of the method, the alternatives are ranked according to the $\bar{D}_i$ score. The higher the $\bar{D}_i$ value, the better the alternative's performance.

$$\bar{D}_i = \sum_{j=1}^{n} w_j^{*} Z_{ij}^{*}, \; i = 1,2,\ldots,m. \qquad (17)$$

In TOPSIS, the positive ideal solution is a solution that maximizes the benefit criterion, which improves as the value increases, and minimizes the cost criterion, which improves as the value decreases. The negative ideal solution maximizes the cost criterion while minimizing the benefit criterion. In other words, while the positive ideal solution includes all the best values that the criteria can achieve, the negative low solution includes all the worst values that the criteria can achieve (Bai and Sarkis, 2013).

4. FINDINGS

In this MCDM-based study, which examines the operational performance of international aviation enterprises, primarily evaluation criteria have been determined. The determination of the most appropriate variables to be used in the evaluation is extremely important for the validity and reliability of the research results. In this study, operational performance variables presented by the EUROCONTROL Performance Review Unit (PRU), which has an active role in the aviation industry, were used. The variables that were weighted and used in the performance evaluation are presented in Table 1. The variables in the table are positive benefit criteria.

Table 1. Evaluation criteria

Code	*Criteria*	*Data source*
C1	Size of controlled airspace in km^2	EUROCONTROL NM
C2	Number of airports with TWR operational unit	ANSP
C3	Total IFR flights controlled by the ANSP	EUROCONTROL NM
C4	% Overflights	EUROCONTROL NM
C5	% Domestic flights	EUROCONTROL NM
C6	% Arr/Dep international flights	EUROCONTROL NM
C7	Total distance (km) controlled by the ANSP	EUROCONTROL NM
C8	Total IFR flight-hours controlled by the ANSP	EUROCONTROL NM/ PRU
C9	Total IFR airport movements controlled by the ANSP	EUROCONTROL NM
C10	Sum of IFR ACC movements	EUROCONTROL NM
C11	Sum of IFR Km controlled by the ACCs	EUROCONTROL NM
C12	Sum of flight-hours controlled by the ACCs	EUROCONTROL NM /PRU

Source: EUROCONTROL (2021)

Within the scope of the research, there are 38 international aviation enterprises as the decision-making unit (DMU), shown in Table 2. The 2021 data of 38 service provider decision-making units (DMU) presented by EUROCONTROL PRU were analyzed using the maximum deviation and EIFTOPSIS method procedure. By applying the equations (4-17) in order, firstly the importance weight scores of the evaluation criteria and then the performance values of the aviation enterprises were calculated.

Table 2. Evaluated decision units

Code	*ANSP Name*	*Country Name*	*Code*	*ANSP Name*	*Country Name*
DMU1	Albcontrol	Albania	DMU20	LFV	Sweden
DMU2	ANS CR	Czech Republic	DMU21	LGS	Latvia
DMU3	ARMATS	Armenia	DMU22	LPS	Slovakia
DMU4	Austro Control	Austria	DMU23	LVNL	Netherlands
DMU5	AVINOR (Continental)	Norway	DMU24	MATS	Malta
DMU6	BHANSA	Bosnia and Herzegovina	DMU25	M-NAV	North Macedonia
DMU7	BULATSA	Bulgaria	DMU26	MOLDATSA	Republic of Moldova
DMU8	Croatia Control	Croatia	DMU27	NATS (Continental)	United Kingdom
DMU9	DCAC Cyprus	Cyprus	DMU28	NAV Portugal (Continental)	Portugal
DMU10	DFS	Germany	DMU29	NAVIAIR	Denmark
DMU11	DHMI	Republic of Turkiye	DMU30	Oro Navigacija	Lithuania
DMU12	DSNA	France	DMU31	PANSA	Poland
DMU13	EANS	Estonia	DMU32	ROMATSA	Romania
DMU14	ENAIRE	Spain	DMU33	SAKAERONAVIGATSIA	Georgia
DMU15	ENAV	Italy	DMU34	skeyes	Belgium
DMU16	Fintraffic ANS	Finland	DMU35	Skyguide	Switzerland
DMU17	HASP	Greece	DMU36	Slovenia Control	Slovenia
DMU18	HungaroControl	Hungary	DMU37	SMATSA	Serbia & Montenegro
DMU19	IAA	Ireland	DMU38	UkSATSE	Ukraine

As can be seen in Figure 1, the total controlled airport movements (0,093) were found to be the most important criterion in the operational performance evaluation. This variable is an indicator for the output of terminal air traffic control covering the first and last stages of the flight (Bilotkach et al., 2015). In addition, total airport movements controlled reflect the relative monetary importance of on-route and terminal area services on average for all European navigation service providers (ENSP) on a total cost basis (Arnaldo et al., 2014). The increase in controlled airport movements leads to a proportionally lower increase in the total cost (Buyle et al., 2018). The percentage of top flights (0,056) was determined as the criterion with the lowest importance. If a flight's departure and arrival airports are located outside the country, that flight is considered an overflight.

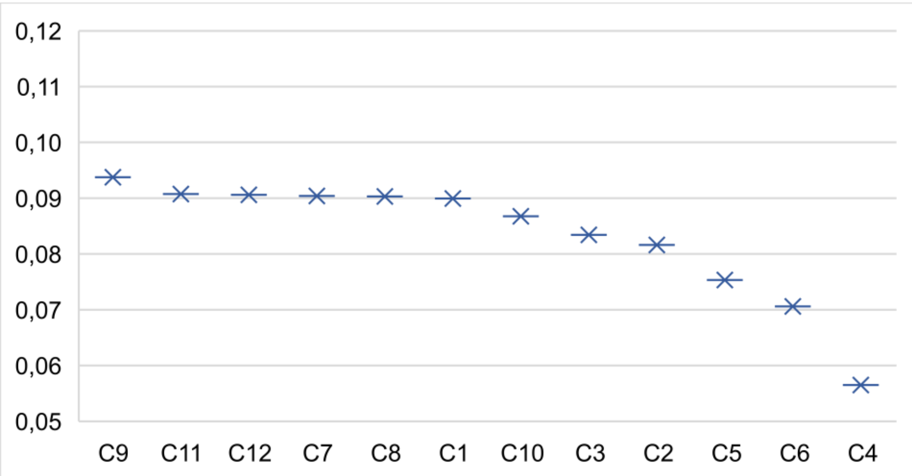

Figure 1. Criterion significance weights

When Figure 2 is examined, the DSNA -France (0,350) aviation enterprise has the highest value in operational performance. ENAIRE – Spain (0,129) and DHMI – Republic of Türkiye (0,129) rank second in the indicator of the highest performance in aviation operations. ARMATS – Armenia (- 0,477), M-NAV – Macedonia (-0,477), and MOLDATSA – Moldova (-0,480) are in the last places by showing the lowest score in operational performance.

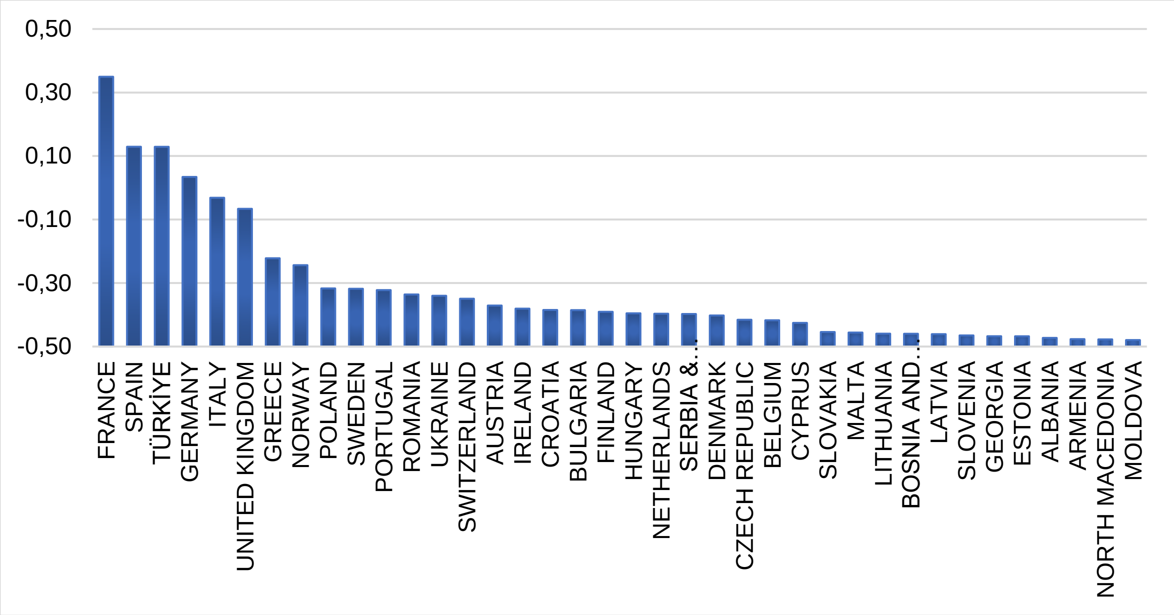

Figure 2. Operational performance ranking

5. CONCLUSION

It is especially important for a free market economy, as problems in the aviation industry can affect both global economic development and international politics. Airline service providers, who view both airlines and passengers as consumers, need to make well-founded decisions on how to improve their competitive position in the market and their operational performance.

In this study, using panel data from EUROCONTROL PRU annual comparison reports, variable importance weights were calculated and the operational performances of international aviation enterprises were measured. The article differs from previous research in that it takes into account the multifaceted nature of the aviation industry and uses a relatively new method, an extended heuristic fuzzy approach. Intuitive fuzzy approaches can minimize the error of uncertainty in multiple decision-making and evaluation situations.

The variable of total airport movements controlled in the results of the research was calculated as the most important variable in the operational performance evaluation. This variable is also important in cost controls. Decision-makers can determine more effective strategies to improve their operational performance over this variable. European countries are taking steps to modernize their aviation infrastructures. This improves cost-effectiveness, spectrum utilization, and the provision of new and more services. According to the results of the study, DSNA, which has the highest operational performance, has taken important steps such as radar vectoring, and reduced separation minimums, especially for the rationalization of aviation infrastructure, while providing a better service to airspace users. In addition, DSNA aims to go further in multinational coordination to achieve an efficient infrastructure. All of the work done by DSNA can be taken as an example by other countries' aviation businesses in improving operational performance. These research results highlight some quantitative issues that need to be considered in depth in the strategy and policy setting of service providers in the aviation industry. It also presents guiding findings that will shed light on decision-makers in improving operational performance.

Indication of limitations in research is important in revealing the importance of the study and providing information to researchers. The most important limitation of this study is that the data used in this research covers only one year and a periodic comparison cannot be made. In future studies, the results of this cross-sectional study can be compared by adding data from the next period to the results of this cross-sectional study and comparing the analyses made with different methods.

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It was declared by the author that scientific and ethical principles have been followed in this study and all the sources used have been properly cited.

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