9. MULTIPLE-CRITERIA APPROACH OF THE OPERATIONAL PERFORMANCE EVALUATION IN THE AIRLINE INDUSTRY: EVIDENCE FROM THE EMERGING MARKETS

Mahmut BAKIR[1],
Şahap AKAN[2],
Kasım KIRACI[3],
Darjan KARABASEVIC[4],
Dragisa STANUJKIC[5],
Gabrijela POPOVIC[6]

Abstract

The main objective of this study is to develop a multiple-criteria decision-making (MCDM) model in order to evaluate the operational performance of airlines operating in emerging markets. In this respect, the manuscript proposes a hybrid multiple-criteria decision-making model based on the integration of the PIPRECIA (PIvot Pairwise RElative Criteria Importance Assessment) and MAIRCA (MultiAttributive Ideal-Real Comparative Analysis) methods. In the proposed model, the PIPRECIA method was used to determine the criteria weights and the MAIRCA method was used to rank alternatives. In order to demonstrate the applicability of the proposed model, a real-life case study was also conducted on the operational performance of 11 airlines in emerging markets. Furthermore, after the application, a sensitivity analysis was conducted in order to ensure the stability of the application and the robustness was confirmed. As a result of the study, the most important performance criterion is found to be operating costs.

Keywords: airline performance; emerging markets; PIPRECIA method; MAIRCA method; MCDM

JEL Classification: D81, L93

---

[1] *Graduate School of Social Sciences, Anadolu University, Eskisehir, Turkey. E-mail: mahmutbakir@anadolu.edu.tr.*

[2] *Graduate School of Social Sciences, Anadolu University, Eskisehir, Turkey. E-mail: sakan@anadolu.edu.tr.*

[3] *Faculty of Aeronautics and Astronautics, Iskenderun Technical University, Hatay, Turkey. E-mail: kasim.kiraci@iste.edu.tr.*

[4] *Faculty of Applied Management, Economics and Finance, University Business Academy in Novi Sad, Belgrade, Serbia. E-mail: darjan.karabasevic@mef.edu.rs.*

[5] *Technical Faculty in Bor, University of Belgrade, Bor, Serbia. E-mail: dstanujkic@tfbor.bg.ac.rs.*

[6] *Faculty of Applied Management, Economics and Finance, University Business Academy in Novi Sad, Belgrade, Serbia. E-mail: gabrijela.popovic@mef.edu.rs.*

1. Introduction

Following the deregulations in 1978, there have been radical changes in the airline industry with liberalization and globalization (Kiracı and Bakır, 2019). Until today, new business models have emerged in this process, markets that are more liberal have been created, airlines have expanded their existing networks and launched flights to new destinations. In this manner, the airline industry has become more competitive and has been under pressure to respond immediately to their competitors' moves to survive (Wu and Liao, 2014). It is essential for airlines to use their existing capacity and resources more effectively and efficiently in order to survive and gain a competitive advantage in the current situation (Jenatabadi and Ismail, 2014). At this point, performance evaluation has come to the fore to answer the question of how efficient and efficient airlines are.

Performance evaluation is important in order for decision-makers (DMs) in businesses to make the right decision, increase the success rate of enterprises and achieve the objectives of the businesses. In addition, it is decisive for enterprises to see and evaluate their shortcomings, to reveal the factors affecting their performance and to establish targets on more realistic basis (Bayyurt, 2007). At this point, it can be said that performance evaluations provide benefits to airlines such as facilitating the execution of many processes. Performance evaluations also support the strategic plans and objectives of the airlines, enabling managers to make objective decisions in many ways, from identifying a number of problems to improving processes and quality (https://www.apqc.org, n.d.). Therefore, airlines can evaluate their internal performance and develop a sectoral insight when measuring performance to keep pace with changes in their environment and gain competitive advantage (Gökdalay and Evren, 2009).

In general, it can be said that airlines apply performance evaluation using many performance metrics (Schefczyk, 1993). These metrics are generally listed as financial, operational and marketing metrics (Grønholdt and Martensen, 2006). While financial and marketing metrics are adaptable to many sectors, operational metrics are unique in terms of reflecting airline characteristics. In other words, as in every sector, the airline sector has its own evaluation criteria due to its sectoral characteristics. These metrics, called Airline-specific Key Performance Indicators (KPIs), are among the pivotal drivers that influence the decisions of airline managers (Kalemba *et al*., 2017). Based on the importance of operational performance indicators in the airline sector, we aim to analyze the operational performance of airlines in the emerging markets. The motivation of this study is as follows. First, emerging countries are making great efforts in terms of economic and technological developments and this dynamism means a great potential for air traffic. However, to the best of our knowledge, there is no study on airline performance analysis in the emerging markets. In this respect, this study will be a first. It is also important to emphasize that “emerging-market economy as a middle-income economy is integrated into the world economy in terms of trade, investment and financial flows but with immature/imperfect market mechanisms and institutions” (Dabrowski, 2019). Finally, although previous studies generally analyzed airlines without any classification, this study analyze the airlines that have applied similar competitive strategies and face similar challenges. We hope that our study will fulfil these gaps.

In this paper, the operational performance of airlines in emerging markets was examined and the MCDM methods were adopted. MCDM methods are used to solve real-life problems including contradictory and usually conflicting criteria (Liou and Tzeng, 2012; Stanujkić and Karabašević, 2019a). The MCDM methods also offer a powerful and practical solution to decision problems involving quantitative or qualitative criteria under uncertainty (Sitorus *et* *al*., 2019). Scholars have used MCDM methods frequently in the past few decades, and many methods have been proposed in this direction. These methods have been adopted to solve real-life problems for different purposes in different sectors (Dožić, 2019; Karabasevic *et al*., 2019; Popovic *et al*., 2019; Naeini *et al*., 2019). In this respect, it is clear that because of the complex and multidimensional nature of airline performance, MCDM methods can be a sufficient and powerful tool to handle this evaluation. In the literature, different MCDM methods have been adopted to conduct performance analysis, and in this study, it was aimed to propose an effective MCDM approach based on PIPRECIA and MAIRCA methods.

This remainder of the paper is structured as follows. Section 2 offers a brief review of the existing literature related to airline operational performance. Section 3 describes the research methodology and material. Section 4 explains the case study consisting of data analysis and results. Section 5 presents a sensitivity analysis. Finally, Section 6 presents conclusions, research limitations, and directions for future studies.

2. Literature Review

In the literature, it is worth noticing that many studies on performance evaluation on airlines have been conducted. In this context, Assaf and Josiannen (2011) analyzed the operational performance of British airlines by focusing on the years 2002-2007. Barros and Peypoch (2009) analyzed the performance of the Association of European Airlines' members between 2000-2005. Wanke *et al.* (2015) analyzed the airlines in Asia for the period 2006-2012. Dinçer *et al.* (2017) analyzed European-based airlines without considering the business model. Wanke and Barros (2016) investigated the operational performance levels of the Latin American airlines by focusing on the 2010-2014 period. Similarly, Gudiel Pineda *et al.* (2018) analyzed the airlines in the US according to their financial and operational performance. Lu *et al.* (2012) examined the relationship between the operational performance and corporate governance of the 30 airlines operating in the US. Zou *et al.* (2012) evaluated the operational performance of major airlines in the US from spring 1995 to winter 2007 (52 quarters) and investigated the impact on the cost structure of airlines. Seufert *et al.* (2017) evaluated the operational performance of leading airlines worldwide between 2007-2013. Yu *et al.* (2017), in their study of global alliances, conducted a performance analysis on members of global airline alliances. Mhlanga *et al.* (2018) investigated the drivers of the operational efficiency of airlines in South Africa and their impact on airline performance.

When we examined the existing studies methodologically, we found that Data Envelopment Analysis (Assaf and Josiannen, 2011; Barbot *et al*., 2008; Kottas and Madas, 2018; Lu *et al*., 2012; Wanke and Barros, 2016), Bootstrapped Truncated Regression (Barros and Peypoch, 2009; Yu *et al*., 2017), Tobit regression analysis (Mhlanga *et al.,* 2018; Saranga and Nagpal, 2016), structural equation modelling (Jenatabadi and Ismail, 2014) and the VaR (Value at Risk) model(Chuang *et al*., 2008) were widely used. In addition, some methods such as Total Factor Productivity (Barbot *et al*., 2008) and MCDM methods (Dinçer *et al*., 2017; Gudiel Pineda *et al*., 2018; Wanke *et al*., 2015) have also been applied successfully in literature for performance evaluation.

In the existing literature, one may see that some studies have been performed at the airline level and some of them performed regional analyses. Moreover, some studies focused on the strategic airline alliances (Kottas and Madas, 2018; Sjögren and Söderberg, 2011; Yu *et al*., 2017). When the research area is examined, the studies are mainly focused on different regions and countries and some studies performed analysis on a global basis (Barbot *et al*., 2008; Chang and Yu, 2012; Scheraga, 2004; Seufert *et al.*, 2017; Wu *et al.*, 2013). In contrast to studies focusing on different countries (Assaf and Josiannen, 2011; Mhlanga *et al.*, 2018; Saranga and Nagpal, 2016; Tavassoli *et al.*, 2014; Zou and Hansen, 2012), regional studies have analyzed airlines in terms of many regions such as Europe (Barros and Peypoch, 2009; Dinçer *et al.*, 2017; Lozano and Gutiérrez, 2014), Asia (Chuang *et al.*, 2008; Wanke *et al.*, 2015), Latin America (Wanke and Barros, 2016) and Africa (Barros and Wanke, 2015). On the other hand, it is found that the existing literature has neglected the emerging markets. However, the importance of emerging markets in the world economy has started to increase gradually. For example, the Asia Pacific region, where China, Indonesia, South Korea and India are located, is witnessing a significant increase in population and in the GDP (Gross Domestic Product). Moreover, the airline sector has achieved great progress in this region and Asia Pacific is reported to be the region with the highest passenger demand (IATA, 2019). In short, it is considered necessary to investigate the operational performance of airlines in emerging markets. In terms of methodology, the MCDM methods are considered to be appropriate for performance evaluations in accordance with the multidimensional structure of performance and the existing literature (Barros and Wanke, 2015; Dinçer *et al.*, 2017; Gudiel Pineda *et al.*, 2018).

When the literature is examined, one may notice that the MCDM methods are frequently used in the airline sector. As stated in Dozic (2019), when the application areas of MCDM problems are considered, there are many applications on airlines, airports, ATM (Air Traffic Management) and others. Service quality assessment (Ardakani *et al.*, 2015; Gupta, 2018), CSR strategy selection (Lee *et al.*, 2018), financial performance analysis (Feng and Wang, 2000; Perçin and Aldalou, 2018), operational performance analysis (Dinçer *et al.*, 2017; Gudiel Pineda *et al.*, 2018), supplier selection (Rezaei *et al.*, 2014), route or location selection (Deveci *et al.*, 2017; Janic and Reggiani, 2002), evaluation of marketing activities (Tsai *et al.*, 2011), etc., are among these applications. In these studies, different MCDM methods have been successfully applied as crisp or fuzzy numbers (Dožić, 2019). Therefore, the MCDM approach proposed in this study can provide a practical solution to evaluate the operational performance of airlines in the emerging markets. Although there are different MCDM methods in the literature, PIPRECIA, which is a weighting method based on the preference of DMs, and MAIRCA method, a newly-developed ranking method, are used in this study. Both methods require low computational time and simple procedures. Moreover, these methods have been successfully applied to a large number of real-life MCDM problems (Arsić *et al.*, 2018; Pamučar *et al.*, 2018a; Stanujkic *et al.*, 2019b).

3. Research Methodology

In this section, theoretical explanations of the proposed PIPRECIA-MAIRCA methodology are presented. In this respect, the PIPRECIA method was used to assign criteria weights, while the MAIRCA method was used as a ranking tool in the performance analysis of airline alternatives. This section also covers the evaluation criteria and the selection process of the airline sample.

3.1. The PIPRECIA Method

There are many weighting methods in the literature, either based on expert evaluations or based on the application of some mathematical algorithms to the decision matrix. One of these methods is the PIPRECIA (Pivot Pairwise Relative Criteria Importance Assessment) method developed by Stanujkic *et al.* (2017). The PIPRECIA method is a subjective weighting method based on judgments reflecting the cognitive attitudes of DMs.

The PIPRECIA method evolved from the ordinary SWARA method to be used in group decision-making situations. The original SWARA method requires the evaluation criteria to be ranked according to their estimated significance (Vesković *et al*., 2018). However, it is believed that the PIPRECIA method, which eliminates this procedure, is more effective as the SWARA method makes evaluations more complex in group decisions (Popović and Mihajlović, 2018). At the same time, since the computation procedures of the SWARA lack the consistency index, the PIPRECIA method offers the possibility to check the consistency of DMs' evaluations through Kendall's Tau or Spearman's Rank Correlation Coefficient (Stanujkic *et al.*, 2019b).

Existing literature shows numerous successful applications of the PIPRECIA method. Stanujkic *et al*. (2017) proposed the PIPRECIA method on case studies of selection of the most appropriate promoter and evaluation of traditional Serbian restaurants. Stević *et al.* (2018) used the SWOT and fuzzy PIPRECIA methods in the MCDM problem, which focused on barcode technology in warehouse systems of brown paper manufacturers. Stanujkic *et al.* (2018a) applied the PIPRECIA and EDAS methods to the problem of laptop selection. Popović and Mihajlović (2018) employed the Extended PIPRECIA method for the evaluation of touristic projects within the scope of tourism development for the Upper Danube Basin. Stanujkic *et al.* (2018b) combined PIPRECIA and WS PLP methods to evaluate hotels' websites. Stanujkic *et al.* (2019b) measured SERVQUAL-based customer satisfaction in traditional restaurants in Zajecar, Republic of Serbia. The PIPRECIA method was used to weight the satisfaction attributes and the alternatives were ranked by the WS PLP method.

Weighting procedures with the PIPRECIA method involves the following computational steps (Popović and Mihajlović, 2018; Stanujkic *et al*., 2017):

Step 1. Determine the set of relevant evaluation criteria. In this step, evaluation criteria are identified and ranked in the descending order (not required) according to their estimated significance.

Step 2. Determine the relative importance (s_j) of the criteria. Starting from the second criterion, s_j coefficients representing the relative importance of each criterion are determined.

$$s_j = \begin{cases} > 1, & if \quad C_j \succ C_{j-1} \\ 1, & if \quad C_j = C_{j-1} \\ < 1, & if \quad C_j \prec C_{j-1} \end{cases} \tag{1}$$

Step 3. Calculate the coefficient k_j. In this step, the coefficient k_j is calculated for each criterion as follows.

$$k_j = \begin{cases} 1 & j = 1 \\ 2 - s_j & j > 1 \end{cases} \tag{2}$$

Step 4. Identify the recalculated weight q_j. In this step, recalculated weight q_j is calculated for the criterion j.

$$q_j = \begin{cases} 1 & j = 1 \\ \dfrac{q_j - 1}{k_j} & j > 1 \end{cases} \tag{3}$$

Step 5. Calculate the relative weights of the evaluation criteria. In this step, the criterion weights reflecting the attitudes of each participant are obtained as follows.

$$w_j = \frac{q_j}{\sum_{k=1}^{n} q_k} \tag{4}$$

where: w_j is the assigned weight of the criterion j. In group decisions, the PIPRECIA method can also be extended as follows.

Step 6. Determine the group relative weights of the criteria.

For a weight assignment application involving group decisions, R different weight forms are obtained from R respondents. Therefore, in order to combine these forms, a simple transformation process is performed by using Eq. (5-6). In this transformation, aggregation is performed based on the geometric mean.

$$w_j^* = \left(\prod_{r=1}^{R} w_j^r\right)^{\frac{1}{R}} \tag{5}$$

$$w_j = \frac{w_j^*}{\sum_{j=1}^{n} w_j^*} \tag{6}$$

where: w_j denotes the aggregated weight and R denotes the number of the respondents.

3.2. The MAIRCA Method

Numerous different methods have been proposed in recent years to deal with continuous and discrete MCDM problems. One of these methods is the MAIRCA (Multi Attributive Ideal-Real Comparative Analysis) method proposed by Gigović *et al.* (2016). The main principle of the MAIRCA method is to consider the gap between theoretical and real ratings in the evaluation of alternatives. The sum of the gap values of each criterion by alternative gives the total gap of each marked alternative. In the order of alternatives, the best-ranked alternative refers to the alternative with the lowest gap value. The fact that this gap is minimal means that real ratings are almost equal to theoretical ratings, thus desirable *(Pamučar et al.*, 2018b).

The MAIRCA method has been used successfully in many MCDM problems in literature. Gigović *et al.* (2016) used geographic information systems (GIS) and MCDM methods in an integrated location problem for ammunition depots. In this direction, the authors investigated the best alternative among suitable locations using DEMATEL and MAIRCA methods. Pamučar *et al.* (2017) discussed the bidder selection problem by combining the integrated DEMATEL-ANP-MAIRCA methods with interval rough numbers (IRN). Pamučar *et al.* (2018b) proposed the DEMATEL and MAIRCA methodology for location selection for the development of the multimodal logistic center in the Danube River. Badi and Ballem (2018) presented the MCDM model including modified BWM (Best-Worst method) and rough MAIRCA methods in a pharmaceutical supplying case study in Libya. Chatterjee *et al.* (2018) focused on the electronics sector and used the MAIRCA method to evaluate suppliers' performance for green supply chain implementation (GSCM). In this study, criterion weights were calculated by rough DEMATEL-ANP methods and suppliers were analyzed by MAIRCA method. Arsić *et al.* (2018) successfully tested the menu selection application for restaurants by hybrid BWM and R'MAIRCA methods. Pamučar *et al.* (2018a) evaluated the process of selecting a level crossing in the Republic of Serbia by FUCOM and MAIRCA methods.

The application steps of the MAIRCA method can be summarized as follows (Gigović *et al.*, 2016; Pamučar *et al.*, 2018b):

Step 1. Formulate the initial decision matrix (*X*). Like other MCDM methods, the first step of the MAIRCA method is to establish a decision matrix containing alternative values by different criteria. Alternative values (x_{ij}) represent the value that the alternative takes according to the *j*th criterion.

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix} \tag{7}$$

Step 2. Identify preferences for the choice of alternatives (P_{A_i}). Theoretically, when choosing alternatives, the DM is neutral in terms of selection probability. In other words, DM does not have any preference over proposed alternatives. So DM assumes all preferences for alternatives have an equal likelihood. The preference ratio of each alternative is as follows.

$$P_{A_i} = \frac{1}{m}; \sum_{i=1}^{m} P_{A_i} = 1, i = 1, 2, \dots, m \tag{8}$$

If the preference probability of each alternative is equal:

$$P_{A_1} = P_{A_2} = \dots = P_{A_m} \tag{9}$$

where: m denotes the total number of the alternatives.

Step 3. Calculate the elements of theoretical assessment matrix (T_p). The third step of the MAIRCA method describes the formation of the theoretical assessment matrix based on the (P_{A_i}). The (T_p) matrix in *nxm* format is constructed by multiplying the weight coefficients (w_i) assigned to the criteria and the preferences of the alternatives.

$$T_p = \begin{array}{c} P_{A_1} \\ P_{A_2} \\ \dots \\ P_{A_m} \end{array} \begin{bmatrix} t_{p11} & t_{p12} & \dots & t_{p1n} \\ t_{p21} & t_{p22} & \dots & t_{p2n} \\ \dots & \dots & \dots & \dots \\ t_{pm1} & t_{pm2} & \dots & t_{pmn} \end{bmatrix} = \begin{bmatrix} P_{A_1}w_1 & P_{A_1}w_2 & \dots & P_{A_1}w_n \\ P_{A_2}w_1 & P_{A_2}w_2 & \dots & P_{A_2 w_n} \\ \dots & \dots & \dots & \dots \\ P_{A_m}w_1 & P_{A_m}w_2 & \dots & P_{A_m}w_n \end{bmatrix} \tag{10}$$

Initially, since the DM is neutral to the likelihood of alternatives, the values of (P_{A_i}) do not vary by the alternative. The (T_p) matrix created in this step is in *nx1* format.

$$T_p = P_{A_i} \begin{array}{c} \begin{array}{cccc} w_1 & w_2 & \dots & w_n \end{array} \\ \begin{bmatrix} t_{p1} & t_{p2} & \dots & t_{pn} \end{bmatrix} \end{array} = P_{A_i} \begin{array}{c} \begin{array}{cccc} w_1 & w_2 & \dots & w_n \end{array} \\ \begin{bmatrix} P_{A_i}w_1 & P_{A_i}w_2 & \dots & P_{A_i}w_n \end{bmatrix} \end{array} \tag{11}$$

where: t_{pi} is the element of theoretical assessment matrix, and n denotes the total number of criteria.

Step 4. Determine the elements of real assessment matrix (T_r). In this step, the real assessment matrix is established by multiplying the elements of the theoretical assessment matrix (T_p) and the initial decision matrix elements.

$$T_r = \begin{bmatrix} t_{r11} & t_{r12} & \cdots & t_{r1n} \\ t_{r21} & t_{r22} & \cdots & t_{r2n} \\ \cdots & \cdots & \cdots & \cdots \\ t_{rm1} & t_{rm2} & \cdots & t_{rmn} \end{bmatrix} \tag{12}$$

The benefit/cost type of the criteria are taken into account when performing this operation and the matrix elements are calculated according to the following formulas.

For the benefit type criteria (preferred maximum criteria values):

$$t_{rij} = t_{pij}\left(\frac{x_{ij} - x_i^-}{x_i^+ - x_i^-}\right) \tag{13.1}$$

For the cost type criteria (preferred minimum criteria values):

$$t_{rij} = t_{pij}\left(\frac{x_{ij} - x_i^+}{x_i^- - x_i^+}\right) \tag{13.2}$$

where: x_{ij}, x_i^+ and x_i^- are elements of the initial decision matrix. Also, x_i^+ denotes the maximum values of the marked criterion and x_i^- denotes the minimum values of the marked criterion.

Step 5. Calculate the total gap matrix (*G*). This matrix is created based on the difference (gaps). In other words, total gap matrix elements are obtained by using the difference between theoretical assessment (T_p) and real assessment (T_r) matrices.

$$G = \begin{bmatrix} t_{p11} - t_{r11} & t_{p12} - t_{r12} & \cdots & t_{p1n} - t_{r1n} \\ t_{p21} - t_{r21} & t_{p22} - t_{r22} & \cdots & t_{p2n} - t_{r2n} \\ \cdots & \cdots & \cdots & \cdots \\ t_{pm1} - t_{rm1} & t_{pm2} - t_{rm2} & \cdots & t_{pmn} - t_{rmn} \end{bmatrix} \tag{14}$$

The gap g_{ij} takes values from the interval g_{ij} [0, ∞) by using Eq. (15):

$$g_{ij} = \begin{cases} 0, & if \;\; t_{pij} > t_{rij} \\ t_{pij} - t_{rij}, & {\scriptstyle if \; t_{pij} > t_{rij}} \end{cases} \tag{15}$$

In this step, since the alternative where the difference between t_{pij} and t_{rij} is the least is the desirable option, approaching g_{ij} to zero makes the alternative more desirable.

Step 6. Obtain the final values of the criteria functions (Q_i) for each alternative. The final values of the criteria functions (Q_i) are obtained by summing the gaps (g_{ij}) for alternatives. In other words, the sum of the *G* matrix elements by the alternatives' forms, Q_i.

$$Q_i = \sum_{j=1}^{n} g_{ij}\,, \qquad i = 1,2,\dots,m \tag{16}$$

4. The Case Study

4.1. Identification of Evaluation Criteria and Sample Selection

This study provides an approach that includes the analysis of airlines called as Full-Service Network Carriers (FSNCs). FSNCs is a business model adopted by airlines that offer scheduled services over a hub-and-spoke network and are often prone to strategic alliances. This business model also successfully applies complex revenue management practices to ensure high profitability. FSNCs also offer passengers a wide range of pre-flight and on-board services in different cabin classes (Efthymiou and Papatheodorou, 2018). The FSNCs considered are given in Table 1.

Table 1

Airline Sample

ICAO Code	Airline	Country
AMX	Aeroméxico	Mexico
CCA	Air China	China
CAL	China Airlines	China
CES	China Eastern Airlines	China
CSN	China Southern Airlines	China
GIA	Garuda Indonesia	Indonesia
GLO	Gol Transportes Aéreos	Brazil
CHH	Hainan Airlines	China
JAI	Jet Airways (India)	India
CDG	Shandong Airlines	China
THY	Turkish Airlines	Turkey

Source: Compiled by authors.

As shown in Table 1, the study covered 11 leading FSNCs from emerging markets. During the sample selection, only the airlines whose data could be accessed were taken into consideration while the secondary data were collected through the Thomson Reuters Eikon database. For the selection of evaluation criteria, the selection criteria are based on existing literature and accessible criteria on the database were adopted. For this purpose, defined criteria are marked as Operating Costs (C_1), Operating Revenues (C_2), Fleet Size (C_3), Load Factor (C_4), Number of Employees (C_5), Passengers Carried (C_6), Available Seat Kilometers (ASK) (C_7), and Revenue Passenger Kilometers (RPK) (C_8). Among these criteria, C_1, C_3 and C_5 are the cost type criteria while the other criteria (C_2, C_4, C_6, C_7, C_8) are beneficial ones. The criteria used in the study and frequently discussed in the literature are given in Table 2.

Table 2

Performance criteria for evaluation of airline operations

Variable	References
Operating Costs (C1)	(Barros and Wanke, 2015) (Barros and Peypoch, 2009) (Scheraga, 2004) (Mhlanga *et al*., 2018)
Operating Revenues (C2)	(Gudiel Pineda *et al.,* 2018) (Wu *et al.*, 2013) (Wu and Liao, 2014)
Fleet Size (C3)	(Chang and Yu, 2012) (Zhu, 2012) (Barros and Wanke, 2015)
Load Factor (C4)	(Shao and Sun, 2016) (Zhu, 2012) (Barros and Wanke, 2015)
Number of Employees (C5)	(Tavassoli *et al.*, 2014) (Barros and Wanke, 2015) (Lee and Worthington, 2014) (Barros and Peypoch, 2009)
Passengers Carried(C6)	(Gudiel Pineda *et al*., 2018) (Sjögren and Söderberg, 2011) (Wu and Liao, 2014)
ASK (C7)	(Lozano and Gutiérrez, 2014) (Yu *et al.*, 2017) (Mhlanga *et al*., 2018) (Gudiel Pineda *et al.*, 2018) (Sjögren and Söderberg, 2011) (Petrović *et al.*, 2018)
RPK (C8)	(Lozano and Gutiérrez, 2014) (Yu *et al.*, 2017) (Mhlanga *et al.,* 2018) (Barros and Wanke, 2015) (Wu *et al.*, 2013) (Barros and Peypoch, 2009) (Scheraga, 2004)

Source: Compiled by authors.

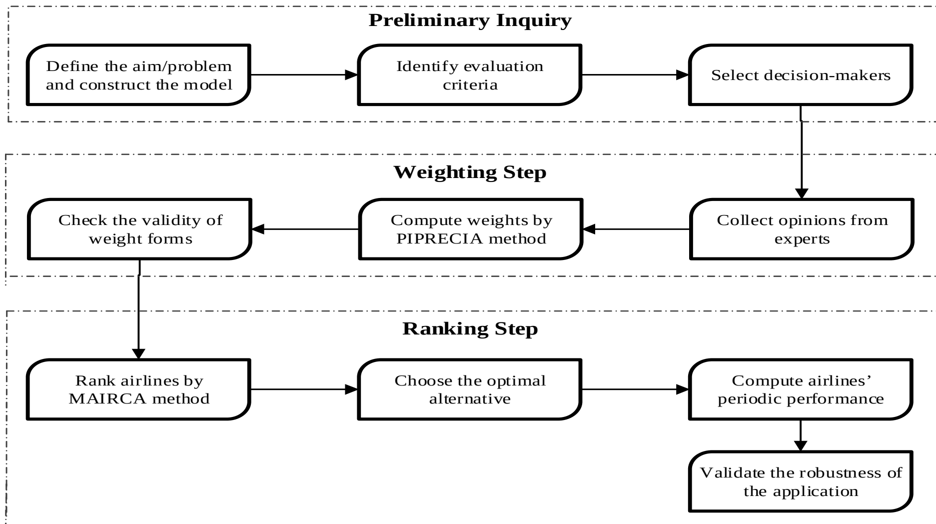
4.2. Numerical Example

In this section, the applicability of the integrated PIPRECIA-MAIRCA methodology is demonstrated by a real-life case study covering the analysis of the operational performance of airlines in emerging markets. In the research, secondary data were used to obtain the data, while 11 airline alternatives were analyzed according to 8 operational criteria. All operational criteria are quantitative. When the research presents a three-stage model (Figure 1), the first stage involves the identification of the research problem, criteria, and decision-makers. At this stage, a group of DMs consisting of 5 researchers with expertise in aviation was identified. In the PIPRECIA method, criteria weights were determined according to the responses of these DMs by e-mail. In the next step, airline alternatives were ranked by the MAIRCA method and analysis was performed for the period from 2010 to 2016. Finally, a sensitivity analysis was performed to confirm the robustness of the application. In the analysis, Microsoft Excel spreadsheet and Jamovi statistical spreadsheet were employed.

After preliminary inquiry as proposed in Figure 1, the calculation of weight coefficients by PIPRECIA was done. In the PIPRECIA method, weights are calculated by using Eq. (1-4) and the procedures applied only for the first DM are given in Table 3 to use paper more sparingly.

Figure 1

Proposed Three-stage Framework for Airline Performance Evaluation



Source: Compiled by authors.

Table 3

The Comparative Criteria Weights for the First DM

	Criteria	s_j	k_j	q_j	w_j
C_1	Operating Costs	1.00	1.00	1.000	0.157
C_2	Operating Revenues	0.90	1.10	0.909	0.143
C_3	Fleet Size	0.95	1.05	0.866	0.136
C_4	Load Factor	0.90	1.10	0.787	0.124
C_5	Number of Employees	0.75	1.25	0.630	0.099
C_6	Passengers Carried	1.20	0.80	0.787	0.124
C_7	ASK (Available Seat Kilometers)	0.75	1.25	0.630	0.099
C_8	RPK (Revenue Passenger Kilometers)	1.15	0.85	0.741	0.117

Source: Compiled by authors.

After determining the criterion weights, the weighting forms are aggregated by using Eq. (5-6) for the case of group decisions. Aggregated final results reflecting the geometric mean of the assessments of the 5 DMs are given in Table 4. The reliability of group responses was checked by Kendall's τ correlation instead of Spearman's ρ since we have a small data set with tied ranks (Field, 2009). Accordingly, since the lowest correlation coefficient was 0.643, the weights are assumed to be consistent. The consistency of DMs' responses is presented in Appendix A.

Table 4

The Overall Group Criteria Weights Determined by PIPRECIA Method

	Criteria	w_j^1	w_j^2	w_j^3	w_j^4	w_j^5	w_j^*	w_j
C_1	Operating Costs	0.157	0.181	0.140	0.150	0.129	0.151	0.151
C_2	Operating Revenues	0.143	0.172	0.133	0.167	0.135	0.150	0.150
C_3	Fleet Size	0.136	0.157	0.127	0.134	0.129	0.136	0.136
C_4	Load Factor	0.124	0.136	0.141	0.127	0.143	0.134	0.134
C_5	Number of Employees	0.099	0.114	0.128	0.111	0.119	0.114	0.114
C_6	Passengers Carried	0.124	0.091	0.122	0.111	0.126	0.115	0.115
C_7	ASK (Available Seat Kilometers)	0.099	0.073	0.102	0.101	0.109	0.097	0.097
C_8	RPK (Revenue Passenger Kilometers)	0.117	0.077	0.107	0.101	0.109	0.102	0.102
	ρ	0.889	0.929	0.643	0.889	0.667		∑=1.00

Source: Compiled by authors.

As one may see in Table 4, C_1 is the most important criteria followed by C_3, C_4, C_6, C_5, C_8, and C_7 criteria. Following the determination of criterion weights, the last stage of our model, MAIRCA application was applied. In this manner, 11 differently sized FSNCs were analyzed based on their operational performance. Although the study covered the 2010-2016 period, application procedures for the 2010 case were given on this paper. For this purpose, the initial decision matrix is established by using Eq. (7). This matrix is given in Table 5.

Table 5

The Initial Decision Matrix for Airlines

Airlines	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
AMX	2011424	2220	44	77.40	10433	11,600	24068	18632
CCA	10540115	12203	255	80.30	24459	46,200	107404	86194
CAL	4108868	4401	65	81.00	16218	10,500	39825	32246
CES	10272846	11089	248	78.00	57096	64,900	119451	93153
CSN	10412371	11317	324	79.20	65085	76,500	140498	111328
GIA	2190476	2027	74	68.80	5745	12,800	29746	20464
GLO	3570655	3972	92	68.90	18776	32,100	45520	31367
CHH	2535431	3211	71	81.70	7959	18,600	39347	32161
JAI	2520651	2844	72	78.60	11328	14,700	34323	26972
CDG	902500	1079	43	80.80	4762	7,900	11484	9278
THY	5324287	5567	127	73.70	17119	29,100	65100	47950

Source: Compiled by authors.

Following the constructing of initial decision matrix, P_{A_i} is determined by using Eq. (8). The value P_{A_i} arises from the assumption that DMs are neutral with respect to the preference probability of alternatives. After calculating these values, theoretical assessment matrix (T_p) was created. This matrix uses Eq. (9) and is in *1xn* format (Table 6).

Following the creation of T_p, the real assessment matrix (T_r) is generated by using Eq. (12) in the next step (Table 7). These matrix elements are formed by multiplying the T_p matrix and the initial decision matrix by taking into account the benefit and cost characteristics of the criteria. In these operations, the corresponding normalization formulas in Eq. (13.1) (for C_2, C_4, C_6, C_7, C_8) and in Eq. (13.2) (for C_1, C_3, C_5) are used.

Table 6

The Theoretical Evaluation ($\boldsymbol{T_p}$) Matrix

	Criteria							
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
$\boldsymbol{T_p}$	0.0137	0.0136	0.0124	0.0122	0.0104	0.0105	0.0088	0.0093

Source: Compiled by authors.

Table 7

The Real Evaluation Matrix ($\boldsymbol{T_r}$)

Airlines	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
AMX	0.012	0.001	0.012	0.008	0.009	0.001	0.001	0.001
CCA	0.000	0.014	0.003	0.011	0.007	0.006	0.007	0.007
CAL	0.009	0.004	0.011	0.012	0.008	0.000	0.002	0.002
CES	0.000	0.012	0.003	0.009	0.001	0.009	0.007	0.008
CSN	0.000	0.013	0.000	0.010	0.000	0.010	0.009	0.009
GIA	0.012	0.001	0.011	0.000	0.010	0.001	0.001	0.001
GLO	0.010	0.004	0.010	0.000	0.008	0.004	0.002	0.002
CHH	0.011	0.003	0.011	0.012	0.010	0.002	0.002	0.002
JAI	0.011	0.002	0.011	0.009	0.009	0.001	0.002	0.002
CDG	0.014	0.000	0.012	0.011	0.010	0.000	0.000	0.000
THY	0.007	0.006	0.009	0.005	0.008	0.003	0.004	0.004

Source: Compiled by authors.

Then, the elements of the total gaps matrix (G) are obtained based on the difference between the theoretical (T_p) and real assessment matrix (T_r) elements by using Eq. (14). The deducted total gap matrix that derives from the difference between these two matrices is given in Table 8.

Table 8

The Total Gap Matrix

Airlines	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
AMX	0.002	0.012	0.000	0.004	0.001	0.010	0.008	0.008
CCA	0.014	0.000	0.009	0.001	0.003	0.005	0.002	0.002
CAL	0.005	0.010	0.001	0.001	0.002	0.010	0.007	0.007
CES	0.013	0.001	0.009	0.003	0.009	0.002	0.001	0.002
CSN	0.014	0.001	0.012	0.002	0.010	0.000	0.000	0.000
GIA	0.002	0.012	0.001	0.012	0.000	0.010	0.008	0.008
GLO	0.004	0.010	0.002	0.012	0.002	0.007	0.006	0.007
CHH	0.002	0.011	0.001	0.000	0.001	0.009	0.007	0.007
JAI	0.002	0.011	0.001	0.003	0.001	0.009	0.007	0.008
CDG	0.000	0.014	0.000	0.001	0.000	0.010	0.009	0.009
THY	0.006	0.008	0.004	0.008	0.002	0.007	0.005	0.006

Source: Compiled by authors.

In the final step of the application, the final values of the criterion function for each alternative are obtained by using Eq. (16). In other words, the sum of the rows of the total gap matrix is obtained for each alternative and the G matrix is formed. The matrix G is given in Table 9 and it should be noted that the best-ranking alternative is the one with the lowest gap value.

Table 9

Airline Ranking with the MAIRCA Method

Airlines	$\boldsymbol{Q}$	Ranking
AMX	0.0452	8
CCA	0.0369	1
CAL	0.0419	5
CES	0.0411	4
CSN	0.0397	3
GIA	0.0536	11
GLO	0.0511	10
CHH	0.0381	2
JAI	0.0434	7
CDG	0.0430	6
THY	0.0459	9

Source: Compiled by authors.

As shown in Table 9, the optimal alternative is CAA for 2010, while GIA is ranked the last. In addition to this evaluation, the airline performance analysis for the research period from 2010 to 2016 was conducted. The criteria weights presented in this paper were transferred to the application of each year, and the results are presented in Table 10.

Table 10

Airlines Performance for the 2010-2016 Period

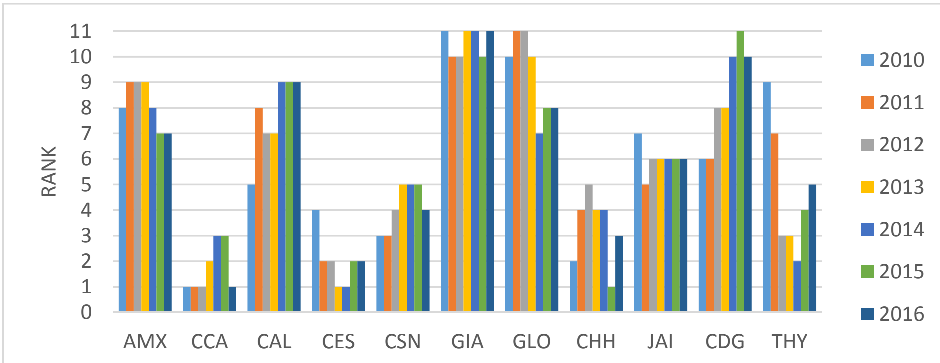
Airlines	2010	2011	2012	2013	2014	2015	2016
AMX	8	9	9	9	8	7	7
CCA	1	1	1	2	3	3	1
CAL	5	8	7	7	9	9	9
CES	4	2	2	1	1	2	2
CSN	3	3	4	5	5	5	4
GIA	11	10	10	11	11	10	11
GLO	10	11	11	10	7	8	8
CHH	2	4	5	4	4	1	3
JAI	7	5	6	6	6	6	6
CDG	6	6	8	8	10	11	10
THY	9	7	3	3	2	4	5

Source: Compiled by authors.

According to Table 10, in general, CCA is the best-ranked airline. Moreover, it is seen that GIA is ranked the last in almost all years. The findings are also illustrated in Figure 2 for a better understanding of the relevant table. Accordingly, one may see that the performances of the airlines vary within the current sample and there are differences in the ranking for the period from 2010 to 2016.

Figure 2

Airline performance by years



Source: Compiled by authors.

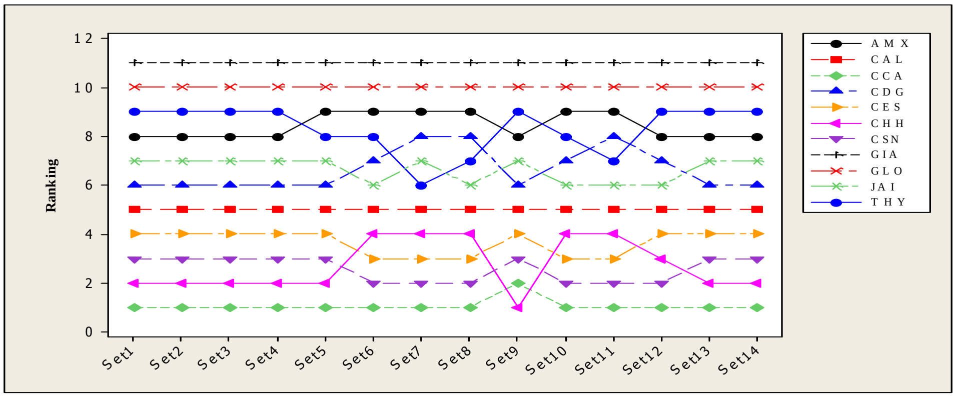
4.3. Sensitivity Analysis

MCDM methods may lack control over the changes in weight coefficients. Therefore, any change in criterion weights can significantly change the order of alternatives in some cases. As a countermeasure, a sensitivity analysis is recommended in many MCDM methods to ensure the stability and robustness of the application (Yazdani *et al.*, 2019). In this part of the study, sensitivity analysis was performed to check the validity and stability of the application.

In this section, different scenarios are created based on the assignment of criterion weights to each criterion. Accordingly, Set1-Set14 scenarios for operational performance analysis were formed by keeping maximum and minimum weights constant. The variation of weights assigned to the criteria is detailed in Appendix 2. As a result of the sensitivity analysis, the scenario-based rankings of Set1-Set14 of the alternatives are given in Figure 3. Based on the analysis, CCA is the best-ranking alternative with the exception of Set9. Additionally, although the ranking of some alternatives has changed in some scenarios, no drastic changes have been observed. To validate these results, Spearman's rank correlation analysis was employed. For all scenarios, the application is considered to be reliable because the rho values are above 0.882 (n=11, p<.001).

Figure 3

Sensitivity Analysis and Scenario-based Rankings



Source: Compiled by authors.

Conclusion

In this study, the integrated PIPRECIA and MAIRCA methodology are proposed to analyze the operational performance of airlines in the emerging markets, as a real-life case study. Although emerging markets are the up-and-coming actors of the growing airline sector, they have been neglected in the existing literature. To the best of our knowledge, performance analysis using airline specific-operational indicators in emerging markets is discussed for the first time in this study. While this paper presenting a three-stage evaluation process, the PIPRECIA application based on the attitudes of 5 DMs was performed to determine the criteria weights. In the next step, 11 emerging markets-origin FSNCs were analyzed according to their operational performance by the MAIRCA method for the period from 2010 to 2016. Finally, the robustness of the results was checked by sensitivity analysis and reliable results were obtained.

Among the methods used in the study, PIPRECIA method was preferred because it is very suitable for group decision-making problems and requires less binary comparisons. Similarly, MAIRCA method was preferred because it was successfully applied to many real-life MCDM problems. Both methods also have simple computational procedures. When the findings of the study were examined, it was found that operating costs were the most effective criterion for operational performance in the observed FSNCs. Then, operating revenues ranks second and fleet size ranks third. These results show that controlling operational costs and revenues in airlines is the driving factor for airline performance and competitive sustainability. Moreover, the fact that the fleet size criterion, which is an important efficiency criterion, comes to the forefront indicates that airlines should use their aircraft more effectively. Moreover, the application results demonstrated that CCA and CES are the best ranking airlines in the research period. On the other hand, the ranking shows us that there are minor changes in the overall ranking of airlines over the years. Finally, in the sensitivity analysis, the stability of the model was ensured and a high correlation was found between the rankings.

The theoretical novelty of the study is twofold. Firstly, the integrated methodology proposed in the study was introduced for the first time in this study. Second, although there are many studies in the existing literature focusing on the performance analysis of airlines in different regions (Barros and Peypoch, 2009; Gudiel Pineda *et al*., 2018; Mhlanga *et al*., 2018; Wanke *et al*., 2015), no performance analysis study has been found for the emerging countries. Considering the growth rates of airlines and the increase in the market shares of the emerging countries, it is predicted that the performance of these airlines will have a major impact on the airline sector in the coming years. Therefore, it is thought that this study will contribute to the existing literature due to the above-mentioned issues.

There are also some lessons for airline managers to be learned from this study. Firstly, the proposed multi-criteria model offers a useful approach for managers to define their company's strengths, weaknesses, and priorities for improvements. In this manner, airlines can be able to monitor their operational performance and their competitors and take these issues into account in future strategies. Additionally, airlines are also growing in the emerging markets. Therefore, in the airline sector where there is intense competition, airlines should apply strict control over their operational costs in order to increase their competitive power and thus survive. In this respect, improvements to the criteria highlighted in this paper, such as operational costs, will pave the way for airlines to become more efficient with available resources.

Like any other study, this one has some limitations. First of all, as earlier mentioned (Gudiel Pineda *et al*., 2018; Yu *et al.*, 2017), the greatest challenge encountered in studies on airline performance is the lack of detailed data. In this study, the variables discussed in the literature were adopted based on their accessibility. Therefore, robust and more reliable findings can be obtained by using more variables in future studies. In addition, it should not be forgotten that the non-financial data and airline sample should be expanded. In future studies, it is also important for the literature to present powerful tools to investigate the factors causing the efficiency and inefficiency of the airlines in the emerging markets. For this purpose, advanced multivariate methods such as Tobit and Truncated Regression analysis can be employed. Finally, this study only represents the relevant research period and observed airline alternatives. Similar studies in the future will contribute both to the enrichment of the literature and validation of the findings.

References

Ardakani, S.S., Nejatian, M., Farhangnejad, M.A. and Nejati, M., 2015. A fuzzy approach to service quality diagnosis. *Marketing Intelligence and Planning*, 33(1), pp.103-119, https://doi.org/10.1108/MIP-02-2013-0035.

Arsić, S.N., Pamučar, D., Suknovic, M. and Janošević, M., 2018. Menu evaluation based on rough MAIRCA and BW methods. *Serbian Journal of Management*, 14(1), pp.27-48, https://doi.org/10.5937/sjm14-18736.

Assaf, A.G. and Josiannen, A., 2011. The operational performance of UK airlines: 2002-2007. *Journal of Economic Studies*, 38(1), pp.5-16, https://doi.org/10.1108/01443581111096114.

Badi, I. and Ballem, M., 2018. Supplier Selection using Rough BWM-MAIRCA model: A case study in Pharmaceutical Supplying in Libya. *Decision Making: Applications in Management and Engineering*, 1(2), pp.16-33, https://doi.org/10.31181/dmame1802016b.

Barbot, C., Costa, Á. and Sochirca, E., 2008. Airlines performance in the new market context: A comparative productivity and efficiency analysis. *Journal of Air Transport Management*, 14(5), pp.270-274, https://doi.org/10.1016/j.jairtraman.2008.05.003.

Barros, C.P. and Peypoch, N., 2009. An evaluation of European airlines' operational performance. *International Journal of Production Economics*, 122(2), pp.525-533, https://doi.org/10.1016/j.ijpe.2009.04.016.

Barros, C.P. and Wanke, P., 2015. An analysis of African airlines efficiency with two-stage TOPSIS and neural networks. *Journal of Air Transport Management*, 44, pp.90-102, https://doi.org/10.1016/j.jairtraman.2015.03.002.

Bayyurt, N., 2007. İşletmelerde performans değerlendirmenin önemi ve performans göstergeleri arasındaki ilişkiler. *Sosyal Siyaset Konferansları Dergisi*, 53, pp.577-592.

Chang, Y.C. and Yu, M.M., 2012. Measuring production and consumption efficiencies using the slack-based measure network data envelopment analysis approach: The case of low-cost carriers. *Journal of Advanced Transportation*, 48(1), pp.15-31, https://doi.org/10.1002/atr.198.

Chatterjee, K., Pamucar, D. and Zavadskas, E.K., 2018. Evaluating the performance of suppliers based on using the R'AMATEL-MAIRCA method for green supply chain implementation in electronics industry. *Journal of Cleaner Production*, 184, pp.101-129, https://doi.org/10.1016/j.jclepro.2018.02.186.

Chuang, I.Y., Chiu, Y.C. and Edward Wang, C., 2008. The performance of Asian airlines in the recent financial turmoil based on VaR and modified Sharpe ratio. *Journal of Air Transport Management*, 14, pp.257-262, https://doi.org/10.1016/j.jairtraman.2008.05.001.

Dabrowski, M., 2019. Can emerging markets be a source of global troubles again?. *Russian Journal of Economics*, 5(1), pp.67-87, https://doi.org/10.32609/j.ruje.5.35506.

Deveci, M., Demirel, N.Ç. and Ahmetoğlu, E., 2017. Airline new route selection based on interval type-2 fuzzy MCDM: A case study of new route between Turkey-North American region destinations. *Journal of Air Transport Management*, 59, pp.83-99, https://doi.org/10.1016/j.jairtraman.2016.11.013.

Dinçer, H., Hacıoğlu, Ü. and Yüksel, S., 2017. Balanced scorecard based performance measurement of European airlines using a hybrid multicriteria decision making approach under the fuzzy environment. *Journal of Air Transport Management*, 63, pp.17-33, https://doi.org/10.1016/j.jairtraman.2017.05.005.

Dožić, S., 2019. Multi-criteria decision making methods: Application in the aviation industry. *Journal of Air Transport Management*, 79, pp.1-22, https://doi.org/10.1016/j.jairtraman.2019.101683.

Efthymiou, M. and Papatheodorou, A., 2018. Evolving airline and airport business models, in Halpern, N. and Graham, A. (Eds.), *The Routledge Companion to Air Transport Management*. New York: Routledge, pp.122-135.

Feng, C.M. and Wang, R.T., 2000. Performance evaluation for airlines including the consideration of financial ratios. *Journal of Air Transport Management*, 6(3), pp.133-142, https://doi.org/10.1016/S0969-6997(00)00003-X.

Field, A., 2009. *Discovering Statistics Using SPSS*. London: SAGE Publications Ltd.

Gigović, L., Pamučar, D., Bajić, Z. and Milićević, M., 2016. The combination of expert judgment and GIS-MAIRCA analysis for the selection of sites for

ammunition depots. *Sustainability*, 8(4), 372, https://doi.org/10.3390/su8040372.
Gökdalay, M.H. and Evren, G., 2009. Havaalanlarının performans analizinde bulanık çok ölçütlü karar verme yaklaşımı. *İTÜDERGİSİ/D*, 8(6), pp.157-168.
Grønholdt, L. and Martensen, A., 2006. Key Marketing Performance Measures. *The Marketing Review*, 6, pp.243-252.
Gudiel Pineda, P.J., Liou, J.J.H., Hsu, C.C. and Chuang, Y.C., 2018. An integrated MCDM model for improving airline operational and financial performance. *Journal of Air Transport Management*, 68, pp.103-117, https://doi.org/10.1016/j.jairtraman.2017.06.003.
Gupta, H., 2018. Evaluating service quality of airline industry using hybrid best worst method and VIKOR. *Journal of Air Transport Management*, 68, pp.35-47, https://doi.org/10.1016/j.jairtraman.2017.06.001.
APQC, 2019. Available at: <https://www.apqc.org/> [accessed on 15 May 2019].
IATA, 2019. Healthy Passenger Demand Continues in 2018 with Another Record Load Factor. [online] Available at: <https://www.iata.org/pressroom/pr/Pages/2019-02-07-01.aspx> [accessed on 29 May 2019].
Janic, M. and Reggiani, A., 2002. An application of the multiple criteria decision making (MCDM) analysis to the selection of a new hub airport. *European Journal of Transport and Infrastructure Research*, 2(2), pp.113-141, https://doi.org/10.18757/ejtir.2002.2.2.3692.
Jenatabadi, H.S. and Ismail, N.A., 2014. Application of structural equation modelling for estimating airline performance. *Journal of Air Transport Management*, 40, pp.25-33, https://doi.org/10.1016/j.jairtraman.2014.05.005.
Kalemba, N., Campa-Planas, F., Hernández-Lara, A.-B. and Sánchez-Rebull, M.V., 2017. Service quality and economic performance in the US airline business. *Aviation*, 21(3), pp.102-110, https://doi.org/10.3846/16487788.2017.1378266.
Karabasevic, D., Popovic, G., Stanujkic, D., Maksimovic, M. and Sava, C., 2019. An Approach for Hotel Type Selection Based on the Single-Valued Intuitionistic Fuzzy Numbers. *International Review*, 1-2, pp.7-14.
Kiracı, K. and Bakır, M., 2019. CRITIC Temelli EDAS Yöntemi İle Havayolu İşletmelerinde Performans Ölçümü Uygulaması. *Pamukkale University Journal of Social Sciences Institute*, Pamukkale Universitesi Sosyal Bilimler Enstitusu Dergisi, 35, pp.157-174, https://doi.org/10.30794/pausbed.421992.
Kottas, A.T. and Madas, M.A., 2018. Comparative efficiency analysis of major international airlines using Data Envelopment Analysis: Exploring effects of alliance membership and other operational efficiency determinants. *Journal of Air Transport Management*, 70, pp.1-17, https://doi.org/10.1016/j.jairtraman.2018.04.014.
Lee, B.L. and Worthington, A.C., 2014. Technical efficiency of mainstream airlines and low-cost carriers: New evidence using bootstrap data envelopment analysis truncated regression. *Journal of Air Transport Management*, 38, pp.15-20, https://doi.org/10.1016/j.jairtraman.2013.12.013.
Lee, K.C., Tsai, W.H., Yang, C.H. and Lin, Y.Z., 2018. An MCDM approach for selecting green aviation fleet program management strategies under multi-resource limitations. *Journal of Air Transport Management*, 68, pp.76-85, https://doi.org/10.1016/j.jairtraman.2017.06.011.

Liou, J.J.H. and Tzeng, G.-H., 2012. Comments on “Multiple criteria decision making (MCDM) methods in economics: an overview. *Technological and Economic Development of Economy,* 18(4), pp.672-695, https://doi.org/10.3846/20294913.2012.753489.

Lozano, S. and Gutiérrez, E., 2014. A slacks-based network DEA efficiency analysis of European airlines’, *Transportation Planning and Technology*, 37(7), pp.623-637, https://doi.org/10.1080/03081060.2014.935569.

Lu, W.M., Wang, W.K., Hung, S.W. and Lu, E.T., 2012. The effects of corporate governance on airline performance: Production and marketing efficiency perspectives. *Transportation Research Part E: Logistics and Transportation Review*, 48(2), pp.529-544, https://doi.org/10.1016/j.tre.2011.09.003.

Mhlanga, O., Steyn, J. and Spencer, J., 2018, The airline industry in South Africa: drivers of operational efficiency and impacts. *Tourism Review*, 73(3), pp.389-400, https://doi.org/10.1108/TR-07-2017-0111.

Pamučar, D., Lukovac, V., Božanić, D. and Komazec, N., 2018. Multi-criteria FUCOM-MAIRCA model for the evaluation of level crossings: case study in the Republic of Serbia. *Operational Research in Engineering Sciences: Theory and Applications*, 1(1), pp.108-129, https://doi.org/10.31181/oresta190120101108p.

Pamučar, D., Mihajlović, M., Obradović, R. and Atanasković, P., 2017. Novel approach to group multi-criteria decision making based on interval rough numbers: Hybrid DEMATEL-ANP-MAIRCA model. *Expert Systems with Applications*, 88, pp.58-80, https://doi.org/10.1016/j.eswa.2017.06.037.

Pamučar, D.S., Tarle, S.P. and Parezanovic, T., 2018. New hybrid multi-criteria decision-making DEMATEL-MAIRCA model: sustainable selection of a location for the development of multimodal logistics centre. *Economic Research-Ekonomska Istrazivanja*, 31(1), pp.1641-1665, https://doi.org/10.1080/1331677X.2018.1506706.

Perçin, S. and Aldalou, E., 2018. Financial Performance Evaluation of Turkish Airline Companies Using Integrated Fuzzy AHP Fuzzy TOPSIS Model. *International Journal of Economics and Administrative Studies*, (18. EYI Special Issue), pp.583-598, https://doi.org/10.18092/ulikidince.347925.

Petrović, D., Puharić, M. and Kastratović, E., 2018. Defining of necessary number of employees in airline by using artificial intelligence tools. *International Review*, 3-4, pp.77-89, doi:10.5937/IntRev1804077P.

Popovic, G. and Mihajlovic, D., 2018. An Mcdm Approach To Tourism Projects Evaluation: The Upper Danube Basin Case. *3rd International Thematic Monograph - Thematic Proceedings: Modern Management Tools and Economy of Tourism Sector in Present Era*, pp.129-141.

Popovic, G., Stanujkic, D., Brzakovic, M. and Karabasevic, D., 2019. A multiple-criteria decision-making model for the selection of a hotel location. *Land Use Policy*, 84, pp.49-58, https://doi.org/10.1016/j.landusepol.2019.03.001.

Rezaei, J., Fahim, P.B.M. and Tavasszy, L., 2014. Supplier selection in the airline retail industry using a funnel methodology: Conjunctive screening method and fuzzy AHP. *Expert Systems with Applications*, 41(18), pp.8165-8179, https://doi.org/10.1016/j.eswa.2014.07.005.

Saranga, H. and Nagpal, R., 2016. Drivers of operational efficiency and its impact on market performance in the Indian Airline industry. *Journal of Air Transport Management*, 53, pp.165-176,

https://doi.org/10.1016/j.jairtraman.2016.03.001.
Schefczyk, M., 1993. Operational Performance of Airlines: An Extesion of Traditional Measurement Paradigms. *Strategic Management Journal*, 14(4), pp.301-317, https://doi.org/10.1002/smj.4250140406.
Scheraga, C.A., 2004. Operational efficiency versus financial mobility in the global airline industry: A data envelopment and Tobit analysis. *Transportation Research Part A: Policy and Practice*, 38(5), pp.383-404, https://doi.org/10.1016/j.tra.2003.12.003.
Seufert, J.H., Arjomandi, A. and Dakpo, K.H., 2017. Evaluating airline operational performance: A Luenberger-Hicks-Moorsteen productivity indicator. *Transportation Research Part E: Logistics and Transportation Review*, 104, pp.52-68, https://doi.org/10.1016/j.tre.2017.05.006.
Shao, Y. and Sun, C., 2016. Performance evaluation of China's air routes based on network data envelopment analysis approach. *Journal of Air Transport Management*, 55, pp.67-75, https://doi.org/10.1016/j.jairtraman.2016.01.006.
Sitorus, F., Cilliers, J.J. and Brito-Parada, P.R., 2019. Multi-criteria decision making for the choice problem in mining and mineral processing: Applications and trends. *Expert Systems with Applications*, 36(3), pp.5432-5435, https://doi.org/10.1016/j.eswa.2018.12.001.
Sjögren, S. and Söderberg, M., 2011. Productivity of airline carriers and its relation to deregulation, privatisation and membership in strategic alliances. *Transportation Research Part E: Logistics and Transportation Review*, 47(2), pp.228-237, https://doi.org/10.1016/j.tre.2010.09.001.
Stanujkic, D., Jevtic, M. and Branislav, I., 2018. An approach for laptop computers evaluation using multiple-criteria decision analysis. *International Scientific Conference UNITECH*, Gabrovo, pp.263-267.
Stanujkić, D. and Karabasevic, D., 2019. An extension of the WASPAS method for decision-making problems with intuitionistic fuzzy numbers: a case of website evaluation. *Operational Research in Engineering Sciences: Theory and Applications*, 1(1), pp.29-39, https://doi.org/10.31181/oresta19012010129s.
Stanujkic, D., Karabasevic, D. and Sava, C., 2018. An Application of the PIPRECIA and WS PLP Methods for Evaluating Website Quality in Hotel Industry. *QUAESTUS Multidisciplinary Research Journal*, 12, pp.190-199.
Stanujkic, D., Karabasevic, D., Zavadskas, E.K., Smarandache, F. and Cavallaro, F., 2019. An approach to determining customer satisfaction in traditional Serbian restaurants'. *Entrepreneurship and Sustainability Issues*, 6(3), pp.1127-1138, https://doi.org/10.9770/jesi.2019.6.3(5).
Stanujkic, D., Kazimieras Zavadskas, E., Karabasevic, D., Smarandache, F. and Turskis, Z., 2017. The use of the pivot pairwise relative criteria importance assessment method for determining the weights of criteria. *Romanian Journal of Economic*, 20(4), pp.116-133.
Stević, Ž., Stjepanović, Ž., Božičković, Z., Das, D.K. and Stanujkić, D., 2018. Assessment of conditions for implementing information technology in a warehouse system: A novel fuzzy PIPRECIA method. *Symmetry*, 10(11), pp.586, https://doi.org/10.3390/sym10110586.
Tavassoli, M., Faramarzi, G.R. and Farzipoor Saen, R., 2014. Efficiency and effectiveness in airline performance using a SBM-NDEA model in the presence of shared

input. *Journal of Air Transport Management*, 14(4), pp.175-178, https://doi.org/10.1016/j.jairtraman.2013.09.001.

Tsai, W.H., Chou, W.C. and Leu, J. Der., 2011. An effectiveness evaluation model for the web-based marketing of the airline industry, *Expert Systems with Applications*. 38(12), pp.15499-15516, https://doi.org/10.1016/j.eswa.2011.06.009.

Vesković, S., Stević, Ž., Stojić, G., Vasiljević, M. and Milinković, S. 2018. Evaluation of the railway management model by using a new integrated model DELPHI-SWARA-MABAC. *Decision Making: Applications in Management and Engineering*, 1(2), pp.34-50, https://doi.org/10.31181/dmame1802034v.

Wanke, P. and Barros, C.P., 2016. Efficiency in Latin American airlines: A two-stage approach combining Virtual Frontier Dynamic DEA and Simplex Regression. *Journal of Air Transport Management*, 61, pp.6-14, https://doi.org/10.1016/j.jairtraman.2016.04.001.

Wanke, P., Pestana Barros, C. and Chen, Z., 2015. An analysis of Asian airlines efficiency with two-stage TOPSIS and MCMC generalized linear mixed models. *International Journal of Production Economics*, 169, pp.110-126, https://doi.org/10.1016/j.ijpe.2015.07.028.

Wu, W.Y. and Liao, Y.K., 2014. A balanced scorecard envelopment approach to assess airlines' performance. *Industrial Management and Data Systems*, 114(1), pp.123-143, https://doi.org/10.1108/IMDS-03-2013-0135.

Wu, Y., He, C. and Cao, X., 2013. The impact of environmental variables on the efficiency of Chinese and other non-Chinese airlines. *Journal of Air Transport Management*, 29, pp.35-38, https://doi.org/10.1016/j.jairtraman.2013.02.004.

Yazdani, M., Chatterjee, P., Pamucar, D. and Abad, M.D., 2019. A risk-based integrated decision-making model for green supplier selection. *Kybernetes*, 49(4), pp.1229-1252, https://doi.org/10.1108/K-09-2018-0509.

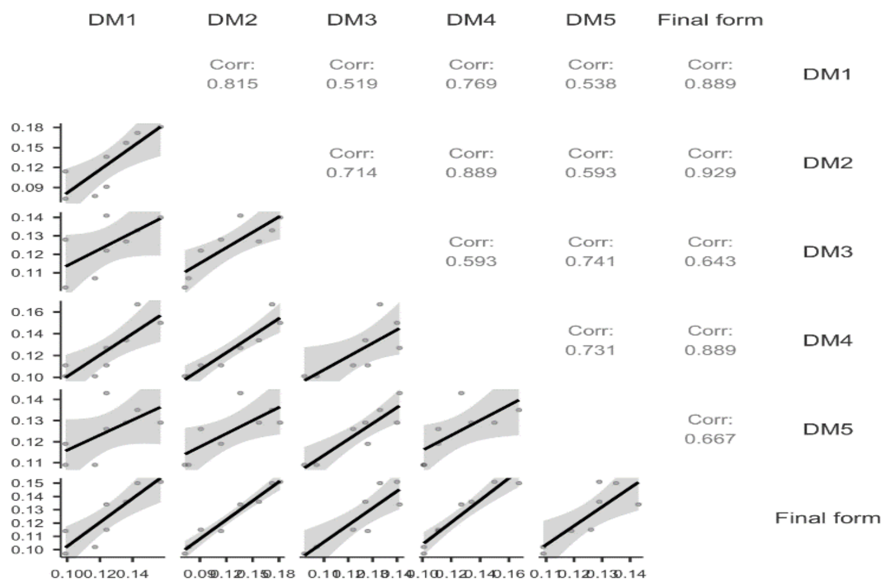
Yu, M.M., Chen, L.H. and Chiang, H., 2017. The effects of alliances and size on airlines' dynamic operational performance. *Transportation Research Part A: Policy and Practice*, 106, pp.197-214, https://doi.org/10.1016/j.tra.2017.09.015.

Zhu, J., 2012. Airlines Performance via Two-Stage Network DEA Approach. *Journal of CENTRUM Cathedra: The Business and Economics Research Journal*, 4(2), pp.260-269.

Zou, B. and Hansen, M., 2012. Impact of operational performance on air carrier cost structure: Evidence from US airlines. *Transportation Research Part E: Logistics and Transportation Review*, 48(5), pp.1032-1048, https://doi.org/10.1016/j.tre.2012.03.006.

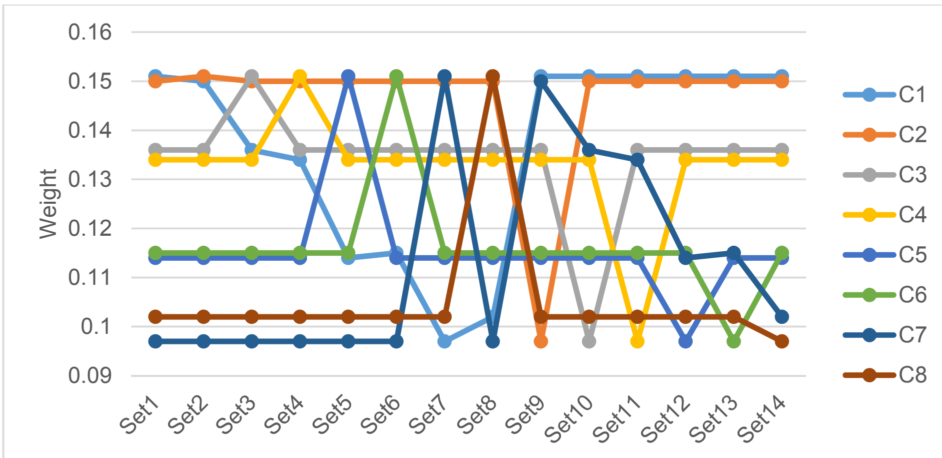
Appendices

Appendix A. Consistency Index for Decision Makers' Responses



Source: Compiled by authors.

Appendix B. Change in the Scenario-based Weights



Source: Compiled by authors.