Journal of Air Transport Management 63 (2017) 45–60

Contents lists available at ScienceDirect

Journal of Air Transport Management

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

A new hybrid simulation-based assignment approach for evaluating airlines with multiple service quality criteria

Mehdi Keshavarz Ghorabaee [a, *], Maghsoud Amiri [a], Edmundas Kazimieras Zavadskas [b], Zenonas Turskis [b], Jurgita Antucheviciene [b]

[a] Department of Industrial Management, Faculty of Management and Accounting, Allameh Tabataba'i University, Tehran, Iran
[b] Department of Construction Technology and Management, Vilnius Gediminas Technical University, Sauletekio al. 11, LT−10223 Vilnius, Lithuania

ARTICLE INFO

Article history:
Received 7 March 2017
Received in revised form
10 April 2017
Accepted 24 May 2017
Available online 1 June 2017

Keywords:
Airline evaluation
Service quality
TOPSIS
COPRAS
WASPAS
EDAS
MCDM

ABSTRACT

Evaluation of airlines based on service quality criteria can help to improve the processes of airlines, and also can give guidance to travel agencies to provide better choices for passengers and tourists. In this study, a hybrid simulation-based assignment approach is proposed to deal with multi-criteria decision-making problems with a group of decision-makers. A probability distribution is used to model decision-makers' opinions and constructing a stochastic decision matrix. Then some efficient multi-criteria decision-making methods are utilized for evaluating alternatives in a simulation process. The proposed approach is applied to a problem of evaluation of five airlines with respect to opinions of 58 experts on 28 criteria. The results show the efficiency of the proposed to handle decision-making problems with a large number of experts. Moreover, the evaluation results are more reliable than the other decision-making approaches because of simulating decision-makers' opinions, using multiple methods and evaluating based on aggregative results.

© 2017 Elsevier Ltd. All rights reserved.

1. Introduction

Service quality can be defined as consumer's overall feeling of the relative superiority or inferiority of an organization and its services which is a result of comparing between customers' expectations and actual services performed (Rust and Oliver, 1993). Service quality is an important factor for airlines and many researchers have applied service quality related theories and methods in the airline industry. Providing high quality services which satisfy passengers and tourists is a core competitive advantage for an airline to reach profitability and sustainable development (Chen, 2008). Most of the studies in airline service quality evaluation presumed the quality of services as a multi-dimensional factor and measured it by a well-known instrument called SERVQUAL (Saha and Theingi, 2009). SERVQUAL is a multi-dimensional measuring instrument which is designed to capture consumer expectations and perceptions of a service in terms of five dimensions including reliability, assurance, tangibles, empathy and responsiveness that are believed to represent the quality of services (Parasuraman et al., 1988).

Because of the multi-dimensional nature of SERVQUAL, this instrument can be integrated with multi-criteria decision-making (MCDM) approaches for evaluation of quality of service (Mardani et al., 2015c). In this field, Awasthi et al. (2011) developed hybrid approach based on fuzzy TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) method and SERVQUAL model for evaluation of transportation service quality. They used the dimensions of the SERVQUAL model as criteria for evaluation and ranking some alternatives. Kuo (2011) proposed a novel interval-valued fuzzy MCDM approach for evaluation of Chinese cross-strait airlines based on service quality criteria. The approach was based on combining VIKOR (in Serbian: VlseKriterijumska Optimizacija I Kompromisno Resenje) and grey relational analysis (GRA) methods, and the SERVQUAL model was used to development of evaluation criteria. In this study, we also use the SERVQUAL model and propose an MCDM approach based on its dimensions. Chou et al. (2011) presented a fuzzy weighted SERVQUAL model and applied it to the evaluation of airline service quality. The dimensions of their SERVQUAL model are used in this study as the evaluation criteria.

It is important to make the evaluation of airlines with multiple

* Corresponding author.
E-mail address: m.keshavarz_gh@yahoo.com (M. Keshavarz Ghorabaee).

http://dx.doi.org/10.1016/j.jairtraman.2017.05.008
0969-6997/© 2017 Elsevier Ltd. All rights reserved.

service quality criteria based on opinions of people who have experience of traveling by the considered airline. Different opinions can result in different evaluations, and it may be more complicated when the number of people increases. The group decision-making approaches are efficient in such situations. In the group decision-making approaches, all the people, who are involved in the evaluation process, are considered as a group of decision-makers. What a majority of individuals prefer should be reflected as a solution in the group decision-making (Kacprzyk, 1986).

In this study, a new hybrid simulation-based assignment approach is developed to deal with multi-criteria decision-making problems with a group of decision-makers. In the proposed approach, the PERT distribution is used to model opinions of the group of decision-makers. This distribution is a special case of the beta distribution and has three parameters (minimum, most likely and maximum) in its standard format. This is a very flexible distribution for modelling expert opinions and can be viewed as a smooth version of the uniform distribution or triangular distribution. After defining a stochastic MCDM problem by this distribution, the Monte Carlo simulation process is started with a predefined number of iterations. In the simulation process, a random MCDM problem generated in each iteration, and the alternatives are evaluated using some MCDM methods. Although the TOPSIS, COPRAS (COmplex PRoportional ASsessment), WASPAS (Weighted Aggregated Sum Product Assessment) and EDAS (Evaluation based on Distance from Average Solution) methods are used in this study, the proposed approach is not limited to these methods, and we aim to increase the accuracy of the evaluation by using multiple methods and reach to more reliable results. The normalized ranking scores obtained from these evaluations at the end of iterations are aggregated and used as the parameters of a linear assignment model. Solving the assignment model, we can determine the final rank of alternatives. The proposed approach is applied to a case study of evaluation and prioritization of airlines with multiple service quality criteria defined in the SERVQUAL model of Chou et al. (2011).

The rest of this paper is organized as follows. In Section 2, we briefly review the literature on the airline service quality and multi-criteria decision-making approaches. In Section 3, the methodological components of the study and the proposed approach are presented in detail. Section 4 describes the application of the proposed approach in evaluation of airlines with multiple service quality criteria. Section 5 presents discussion, and finally conclusions and future directions are presented in Section 6.

2. Literature review

In this section, we present a brief review of some studies on airline service quality and multi-criteria decision-making methods.

2.1. Airline service quality

There have been many studies in the field of airline service quality and the researchers have worked on different aspect of this field and used different methodologies in their studies. In the following we summarize some of the important studies in this field.

Tsaur et al. (2002) applied the fuzzy set theory for evaluation of the service quality of airline. They used the analytic hierarchy process (AHP) method for determination of criteria weights. Then the TOPSIS method is utilized for ranking the alternatives. The dimensions of the SERVQUAL model were used to define the evaluation criteria, and the tangibles and empathy were found as the most and the least important criteria of their study, respectively.

Park et al. (2004) studied on understanding of air passengers' behavioral intentions by testing a conceptual model. Their model considers some variables including service perception, service expectation, airline image, passenger satisfaction, service value and behavioral intentions simultaneously. They applied path analysis via maximum likelihood estimator to data collected from Korean passengers, and found that passenger satisfaction, service value and airline image have a direct effect on air passengers' behavioral intentions.

Chen and Chang (2005) examined the gaps between the service expectations of passengers and two other variables of a Taiwanese airline: the real service received and the perceptions of the expectations by frontline managers and employees. Then for determining areas for improvement, they applied the importance-performance analysis to construct service attribute evaluation maps. Results showed that the passengers were more concerned about the responsiveness and assurance dimensions from airline frontline staff. The tangibles dimension was identified as an important dimension for evaluation of in-flight service quality.

Pakdil and Aydın (2007) studied on expectations and perceptions in airline services. Based on data collected at a Turkish airline, they measured airline service quality using a weighted SERVQUAL model and factor analysis. The results of their research showed that the responsiveness was the most important dimension and the availability was the least important dimension of service quality. The educational level of passengers was an important variable in their study affecting the expectations and perceptions of them.

An and Noh (2009) investigated the impact of the in-flight service quality on airline customer satisfaction and loyalty. Data from two classes of passengers including prestige (business) and economy were analyzed in their study. The results showed that different factors are important in the in-flight service quality according to the passengers' class. The findings implied that different delivery strategies should be chosen by airline companies' in-flight service based on the passengers' class.

Liou et al. (2011) applied a modified VIKOR method to improve service quality of domestic airlines in Taiwan. Their model helps decision-makers to identify the gaps between alternatives and aspired levels in practice. To establish a comprehensive service quality evaluation framework and reduce the gaps for achieving the aspired-level, a large sample was used by them. They also provided some managerial implications to improve the level of service quality of different airlines.

Baker (2013) studied on the service quality and customer satisfaction of the top 14 U.S. airlines between 2007 and 2011. His study had two objectives: comparison of customer satisfaction and service quality based on service quality dimensions of the airlines and examination of the relationships between the dimensions of service quality and passengers' satisfaction. Implications related to operating costs, market share, infrastructure and customer service confirmed that the service quality of low cost airlines was higher than that of traditional legacy airlines.

Muturi et al. (2013) examined the impact of airline service quality on passenger satisfaction and loyalty in Uganda. Their study used random sampling technique and with 303 respondents. The results of their study showed that the quality of pre-flight, in-flight and post-flight services had a statistically significant effect on passenger satisfaction, and also passenger satisfaction had a significant effect on passenger loyalty. They suggested that airlines should consider different strategies based on characteristics of the customers such as occupation, age, gender and education level, to improve their service quality.

Choi et al. (2015) applied a service quality-adjusted data envelopment analysis (SQ-adjusted DEA) to study operational efficiency of US airlines. They found that, in the long-term, a focus on service quality can help to increase customer satisfaction and improve service productivity and overall organizational performance even though there were short-term tradeoffs between service quality and productivity. They also showed that the proposed SQ-adjusted DEA was better than the standard DEA to explore service productivity.

Suki (2014) examined the impact of airline service quality dimensions such as terminal tangibles, empathy and airline tangibles on satisfaction levels of customers in Malaysia. The other investigation of the research was related to the relationship between the levels of satisfaction and the general perceptions about service quality. The relationship between customer satisfaction and airline service quality was shown by using structural equation modeling (SEM) approach. Moreover, the results revealed that empathy highly affects customer satisfaction.

Liou et al. (2016) applied the multivariate statistical analysis and multi-criteria decision-making methods to the improvement of service quality. The rough set theory with a flow graph approach was used by them to identify customer attitudes towards service quality and a large sample of airline customers was used to define a set of rules. They demonstrated that the proposed approach can assist in identifying the needs of customers and determining their characteristics and can help managers to develop airline strategies for improving the quality of services and satisfying customers' needs.

Chen (2016) proposed an approach to select airline service quality improvement criteria for the Taiwanese airline industry. A combined MCDM model based on decision-making trial and evaluation laboratory (DEMATEL) and analytic network process (ANP) is utilized for the selection process. The proposed approach provides a direction for airlines to measure and improve their service quality for developing their competitive advantages.

2.2. Multi-criteria decision-making approaches

Many studies have been conducted in the field of MCDM methods during the past years. These methods have been applied to many problems in science and engineering. In the following, because of using the TOPSIS, COPRAS, WASPAS and EDAS methods in the proposed approach, we briefly review some studies on these methods. However, there are some other MCDM methods like ARAS (Additive Ratio ASsessment), VIKOR and MULTIMOORA (abbreviation of 'multi-objective optimization by ratio analysis plus the full multiplicative form') which have been widely used. Interested readers are referred to the review articles (Mardani et al., 2015a, 2015b, 2016a, 2016b, 2016c).

The TOPSIS method is one of the popular MCDM methods which was proposed by Hwang and Yoon (1981). This method has been extended in many types of uncertain environments. A fuzzy extension of TOPSIS method was introduced by Chen (2000) and has been applied to many problems till now. Some other extensions of this method in fuzzy environment were proposed by Jahanshahloo et al. (2006) and Wang and Elhag (2006). Moreover, this method has been extended in the other types of fuzzy sets such as intuitionistic fuzzy sets (Boran et al., 2009), interval-valued fuzzy sets (Chen and Tsao, 2008), interval-valued intuitionistic fuzzy sets (Ye, 2010), interval type-2 fuzzy sets (Chen and Lee, 2010) and hesitant fuzzy sets (Beg and Rashid, 2013; Xu and Zhang, 2013). This method and its extensions have been used in many studies to deal with multi-criteria decision-making problems. Interested readers are referred to the review performed by Zavadskas et al. (2016).

The COPRAS method which was proposed by Zavadskas et al. (1994) has been applied to many MCDM problems. Das et al. (2012) proposed a framework by integrating fuzzy AHP and COPRAS methods to measure relative performance of Indian technical institutions. Mulliner et al. (2013) applied the COPRAS method to a multi-criteria decision-making problem of sustainable housing affordability in three residential areas. Tavana et al. (2013) developed a hybrid MCDM approach for social media platform selection using the fuzzy ANP method and extended COPRAS method with grey numbers. Nguyen et al. (2015) used a fuzzy linguistic preference based AHP and integrated it with the fuzzy COPRAS for machine tool evaluation. Mulliner et al. (2016) conducted a comparative analysis of some MCDM methods for the process of sustainable housing affordability assessment. Rathi and Balamohan (2016) developed a mathematical model based on the COPRAS method for fuzzy multi-criteria group decision making with subjective evaluation. Mousavi-Nasab and Sotoudeh-Anvari (2017) proposed a hybrid MCDM approach based on the data envelopment analysis, TOPSIS and COPRAS methods and applied it to a material selection problem. A review on applications and extensions of the COPRAS method was performed by Stefano et al. (2015).

The WASPAS method is a relatively new method which was proposed and optimized by Zavadskas et al. (2012). This method has been used by many researchers in the past years. Madić et al. (2015) applied the WASPAS method to the selection of cutting inserts for aluminum alloys machining. Ghorshi Nezhad et al. (2015) proposed a hybrid MCDM approach based on the step-wise weight assessment ratio analysis (SWARA) and WASPAS method for planning high tech industries. Chakraborty et al. (2015) used the WASPAS method to solve some MCDM problems in manufacturing environment. Hashemkhani Zolfani et al. (2015) applied a hybrid SWARA-WASPAS approach for evaluation of strategies in multiple Nash equilibriums. Turskis et al. (2015) developed a hybrid model based on the fuzzy AHP and WASPAS methods for construction site selection. Bozorg-Haddad et al. (2016) used WASPAS and evolutionary algorithms for benchmarking in optimal reservoir optimization problems. The WASPAS method has also been applied to other areas such as asset redevelopment (Pavlovskis et al., 2016), green supplier selection (Keshavarz Ghorabaee et al., 2016a; Yazdani et al., 2016), maintenance performance analysis (Ighravwe and Oke, 2016) and personnel selection (Karabašević et al., 2016).

The EDAS method is a new and efficient method which was proposed by Keshavarz Ghorabaee et al. (2015) for inventory classification problem. Keshavarz Ghorabaee et al. (2015) demonstrated the efficiency of this method for solving MCDM problems. A fuzzy extension of this method was proposed and applied to the supplier selection problem (Keshavarz Ghorabaee et al., 2016b). Furthermore, the EDAS method has been extended using grey interval numbers (Stanujkic et al., 2017), interval type-2 fuzzy sets (Keshavarz Ghorabaee et al., 2017) and intuitionistic fuzzy sets (Kahraman et al., 2017). Peng and Liu (2017) developed some algorithms for soft decision-making with neutrosophic sets based on the EDAS method, new similarity measure and level soft set. Stević et al. (2016) proposed a hybrid MCDM approach based on the AHP and EDAS methods for logistics evaluations. Turskis and Juodagalvienė (2016) used the EDAS method to propose a hybrid MCDM approach for assessing a stairs shape for dwelling houses.

3. Methodology

The proposed approach has a framework with different steps which need to be elucidated. In this section, preliminaries of the proposed approach are presented first, and then we describe the steps and framework of it.

3.1. Preliminaries

As previously mentioned, the PERT distribution and multi-criteria decision-making methods are the main components of the proposed approach. In the following, we define the PERT distribution and present the steps of using the considered MCDM methods.

3.1.1. PERT distribution

A PERT distribution is a modification to the beta distribution. The beta distribution has two parameters (α_1 and α_2) and its domain is between zero and one. The probability density function (PDF) of the beta distribution is as follows (Gullco and Anderson, 2009):

$$Beta(x;\alpha_1,\alpha_2)=\frac{\Gamma(\alpha_1+\alpha_2)}{\Gamma(\alpha_1)\Gamma(\alpha_2)}x^{\alpha_1-1}(1-x)^{\alpha_2-1} \tag{1}$$

where,

$$\Gamma(z)=\int_0^\infty x^{z-1}e^{-x}dx \tag{2}$$

However, the PERT distribution is defined by its minimum, most likely and maximum values which can be any real numbers (Murray, 2004; Vally et al., 2014). Suppose that a, b and c denote the minimum, most likely and maximum values of a PERT distribution, respectively. Then the equation of the PDF of a PERT distribution is related to the beta distribution as follows:

$$PERT(x;a,b,c)=Beta(x;\alpha_1,\alpha_2)\times(c-a)+a \tag{3}$$

where,

$$\alpha_1=\frac{(\mu-a)\times(2b-a-c)}{(b-\mu)\times(c-a)} \tag{4}$$

$$\alpha_2=\frac{\alpha_1\times(c-\mu)}{\mu-a} \tag{5}$$

$$\mu=\frac{a+(\gamma\times b)+c}{\gamma+2} \tag{6}$$

In the PERT distribution γ is the weighting factor of the mean (μ) and can affect the shape of distribution. The value of this factor is equal to four (γ=4) in the standard PERT distribution (Vose, 2008). It should be noted that the standard version of PERT distribution is used in this research.

In comparison with the triangular distribution, the PERT distribution gives a more natural shape. Moreover, the standard deviation of the PERT distribution is less sensitive to the estimate of the extreme (minimum and maximum) values. Therefore, it is not influenced as much by these values, especially if the distribution is skewed (Murray, 2004).

This distribution is very useful to model expert opinion (Murray, 2004; Vally et al., 2014; Vose, 2008). As an example, Fig. 1 shows the PDF of a standard PERT distribution with parameters a = 4, b = 7 and c = 13.

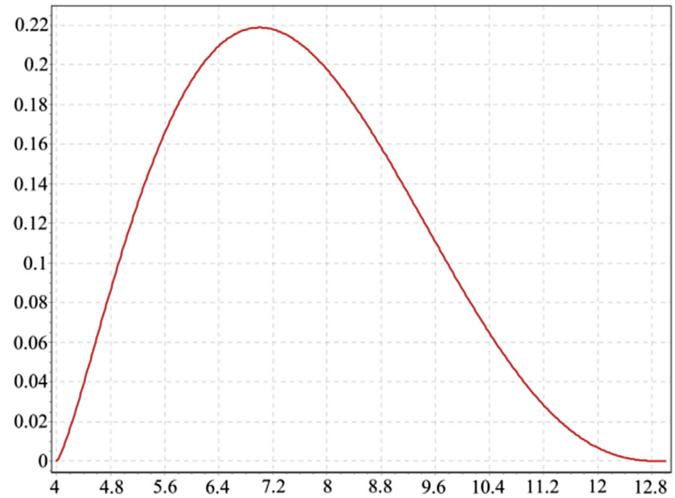

Fig. 1. An example of the PDF of a PERT distribution.

3.1.2. MCDM methods

The proposed approach is based on using multiple MCDM methods to increase the accuracy and reliability of the evaluation results. Here, four efficient MCDM methods including TOPSIS, COPRAS, WASPAS and EDAS are used in this research for evaluation of alternatives. However, the proposed approach is not limited to these methods. Any of these four methods can be replaced with other MCDM method, and also we can use another method together with these four methods, provided that the method has similar nature. However, in this study, we try to consider some old and new MCDM methods which have been applied in this field. Accordingly, the TOPSIS and COPRAS methods are chosen as two old MCDM methods which have been widely used by many researchers in the past years, and the WASPAS and EDAS methods are selected as two new methods which have been recently given scholarly attention. We have briefly reviewed some studies which used these four methods in decision-making processes. In this subsection, the steps of using these methods are presented. Suppose that we have a multi-criteria decision-making problem with n alternatives and m criteria, and the decision-matrix is defined as follows:

$$X=\begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1j} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2j} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & x_{i2} & \cdots & x_{ij} & \cdots & x_{im} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nj} & \cdots & x_{nm} \end{bmatrix} \tag{7}$$

In this decision-making problem, x_{ij} shows the performance value (rating) of i th alternative with respect to j th criterion (i=1,2, …,n and j = 1,2, …,m). Also, w_j is used to define the weight of j th criterion, and $\sum_{j=1}^{m}w_j=1$. According to the mentioned definition, many MCDM methods can be used for evaluating and ranking of alternatives. In the following, the steps of TOPSIS, COPRAS, WASPAS and EDAS methods are summarized.

3.1.2.1. TOPSIS method.

TOPSIS method was presented by Hwang and Yoon (1981). The process of evaluation of alternatives in this method is based on the distance of them from the ideal and anti-ideal (nadir) solution. The procedure of the TOPSIS method is presented in the following steps.

Step 1. Determine the normalized values of the decision-matrix, as follows:

$$\bar{x}_{ij}=\frac{x_{ij}}{\sqrt{\sum_{i=1}^{n}x_{ij}^2}} \tag{8}$$

Step 2. Use the following equation to calculate the weighted normalized values:

$$\bar{x}_{ij}^{w} = w_j \times \bar{x}_{ij} \tag{9}$$

Step 3. Obtain the ideal and anti-ideal solutions using the calculated weighted normalized values shown as follows:

$$I^{*} = \left\{\bar{x}_1^{w*}, \dots, \bar{x}_m^{w*}\right\} = \left\{\left(\max_i \bar{x}_{ij}^{w}\middle| j\in BC\right), \left(\min_i \bar{x}_{ij}^{w}\middle| j\in NC\right)\right\} \tag{10}$$

$$I^{-} = \left\{\bar{x}_1^{w-}, \dots, \bar{x}_m^{w-}\right\} = \left\{\left(\min_i \bar{x}_{ij}^{w}\middle| j\in BC\right), \left(\max_i \bar{x}_{ij}^{w}\middle| j\in NC\right)\right\} \tag{11}$$

where BC and NC are the sets of beneficial and non-beneficial criteria, respectively.

Step 4. Calculate the Euclidean distance of alternatives from the ideal (D_i^*) and anti-ideal (D_i^-) solutions:

$$D_i^{*} = \sqrt{\sum_{j=1}^{m}\left(\bar{x}_{ij}^{w} - \bar{x}_j^{w*}\right)^2} \tag{12}$$

$$D_i^{-} = \sqrt{\sum_{j=1}^{m}\left(\bar{x}_{ij}^{w} - \bar{x}_j^{w-}\right)^2} \tag{13}$$

Step 5. Calculate the closeness coefficient (CC_i) of each alternative, as follows:

$$CC_i = \frac{D_i^-}{D_i^* + D_i^-} \tag{14}$$

Step 6. Rank the alternatives in decreasing order of calculated closeness coefficient values.

3.1.2.2. COPRAS method. The COPRAS method is an MCDM method in which direct and proportional dependence of significance and priority of investigated alternatives on a system of criteria are considered (Zavadskas et al., 1994). This method has four steps as follows:

Step 1. Compute the weighted normalize values the decision-matrix elements as follows:

$$\bar{x}_{ij} = \frac{w_j x_{ij}}{\sum_{i=1}^{n} x_{ij}} \tag{15}$$

Step 2. Calculate the sum of weighted normalized values of each alternative with respect to beneficial (S_i^+) and non-beneficial (S_i^-) criteria using the following equations:

$$S_i^{+} = \sum_{j\in BC} \bar{x}_{ij} \tag{16}$$

$$S_i^{-} = \sum_{j\in NC} \bar{x}_{ij} \tag{17}$$

where BC and NC are the sets of beneficial and non-beneficial criteria, respectively.

Step 3. Determine the relative significance of each alternative ($\Re_i$) according the values of S_i^+ and S_i^-, and calculate the utility degree ($\mathscr{N}_i$) of each alternative as follows:

$$\Re_i = S_i^{+} + \frac{\sum_{i=1}^{n} S_i^-}{S_i^- \sum_{i=1}^{n} \frac{1}{S_i^-}} \tag{18}$$

$$\mathscr{N}_i = \frac{\Re_i}{\max_k \Re_k} \tag{19}$$

It should be noted that if we have no non-beneficial criteria in the MCDM problem, the second term of Eq. (18) is omitted, i.e. $\Re_i = S_i^+$.

Step 4. Determine the rank of alternatives according to the values of the relative significance ($\Re_i$) or utility degree ($\mathscr{N}_i$). The greater the value of $\Re_i$ (or $\mathscr{N}_i$), the higher the priority.

3.1.2.3. WASPAS method. Zavadskas et al. (2012) proposed the WASPAS method as an MCDM method by integration of the weighted sum model (WSM) and weighted product model (WPM). The following steps are used in this method for decision-making process.

Step 1. Calculate normalized performance values by linear normalization, as follows:

$$\bar{x}_{ij} = \begin{cases} \dfrac{x_{ij}}{\max_i x_{ij}} & \text{if } j\in BC \\ \dfrac{\min_i x_{ij}}{x_{ij}} & \text{if } j\in NC \end{cases} \tag{20}$$

where BC and NC are the sets of beneficial and non-beneficial criteria, respectively.

Step 2. Determine the measures of WSM ($\mathfrak{V}_i^{(1)}$) and WPM ($\mathfrak{V}_i^{(2)}$) for each alternative as follows:

$$\mathfrak{V}_i^{(1)} = \sum_{j=1}^{m} w_j \bar{x}_{ij} \tag{21}$$

$$\mathfrak{V}_i^{(2)} = \prod_{j=1}^{m} \left(\bar{x}_{ij}\right)^{w_j} \tag{22}$$

Step 3. Compute the combined measure of the WASPAS method for each alternative as follows:

$$\mathfrak{V}_i = \vartheta \mathfrak{V}_i^{(1)} + (1-\vartheta)\mathfrak{V}_i^{(2)} \tag{23}$$

In the above equation, ϑ is the trade-off parameter of the WASPAS method and can be varied between zero and one. Using $\vartheta = 1$ leads to weighted sum model, and when $\vartheta = 0$ WASPAS method is transformed to weighted product model.

Step 4. Determine rank of the alternatives according to decreasing values of $\mathfrak{V}_i$.

3.1.2.4. EDAS method. The EDAS method is a new and efficient MCDM method which proposed by Keshavarz Ghorabaee et al.

(2015). Evaluation process in this method is based on positive and negative distances from the average solution. The steps of using this method are presented as follows:

Step 1. Determine the average solution elements ($\mathscr{T}_j$) with respect to each criterion shown as follows:

$$\mathscr{T}_j = \frac{\sum_{i=1}^{n} x_{ij}}{n} \tag{24}$$

Step 2. Calculate the positive distance ($\mathscr{P}d_{ij}$) and negative distance ($\mathscr{N}d_{ij}$) of each elements of the decision-matrix from the calculated elements of the average solution using the following equations:

$$\mathscr{P}d_{ij} = \begin{cases} \dfrac{max(0, x_{ij} - \mathscr{T}_j)}{\mathscr{T}_j} & if\ j \in BC \\ \dfrac{max(0, \mathscr{T}_j - x_{ij})}{\mathscr{T}_j} & if\ j \in NC \end{cases} \tag{25}$$

$$\mathscr{N}d_{ij} = \begin{cases} \dfrac{max(0, \mathscr{T}_j - x_{ij})}{\mathscr{T}_j} & if\ j \in BC \\ \dfrac{max(0, x_{ij} - \mathscr{T}_j)}{\mathscr{T}_j} & if\ j \in NC \end{cases} \tag{26}$$

where BC and NC are the sets of beneficial and non-beneficial criteria, respectively.

Step 3. Compute the weighted summation of the calculated positive and negative distances for each alternative as follows:

$$\mathscr{SP}_i = \sum_{j=1}^{m} w_j \mathscr{P}d_{ij} \tag{27}$$

$$\mathscr{NP}_i = \sum_{j=1}^{m} w_j \mathscr{N}d_{ij} \tag{28}$$

Step 4. Calculate the normalized values of $\mathscr{SP}_i$ and $\mathscr{NP}_i$ as follows:

$$\mathscr{SP}_i^{(n)} = \frac{\mathscr{SP}_i}{\max_k \mathscr{SP}_k} \tag{29}$$

$$\mathscr{NP}_i^{(n)} = 1 - \frac{\mathscr{NP}_i}{\max_k \mathscr{NP}_k} \tag{30}$$

Step 5. Calculated the appraisal score of each alternative using the following equation:

$$\mathscr{A}s_i = \frac{1}{2}\left(\mathscr{SP}_i^{(n)} + \mathscr{NP}_i^{(n)}\right) \tag{31}$$

Step 6. Rank the alternatives according to decreasing values of $\mathscr{A}s_i$.

3.1.3. Monte Carlo simulation

Monte Carlo simulation is a method that commonly incorporates using computer-generated random numbers and theory of probability into the solving process of problems. Usually the Monte Carlo simulation is an alternative to analytical mathematics which uses repeated sampling to determine the properties of some phenomenon or behavior (Chang, 2010). In this method, the computational model (or any other type of model) should be run in a large number of iterations with random sampling. Random values are generated for each input variable in each iteration, and running the model results random outcomes on each output variable (Thomopoulos, 2012). Although there have been many studies on the Monte Carlo simulation and its application in different fields of science and engineering, most of them tend to use a common pattern with the following steps:

1. Determine the domain of the variables of the model.
2. Generate random values over the domain of the variables from a probability distribution.
3. Run the computational steps of the model iteratively and obtain the values of the output variables.
4. Aggregate the results of running in different iterations.

3.2. Proposed approach

In this section, we present a simulation-based approach based on the PERT distribution, the described MCDM methods (TOPSIS, COPRAS, WASPAS and EDAS) and a mathematical assignment model for evaluation of airlines with multiple service quality criteria based on the opinion of multiple experts (decision-makers). Suppose that we have p decision-makers. We describe the steps of the proposed approach as follows:

Step 1. Design the evaluation problem by determination of alternatives and evaluation criteria.Choosing suitable criteria for evaluation process is very important in this step and every decision-maker should be in agreement on the chosen criteria because in the following step the alternatives are evaluated with respect to these criteria by each decision-maker.

Step 2. Get the score of the evaluation criteria from each decision-maker.The 9-point Likert scale is used in this step to elicit the opinion of the decision-makers. Let us denote by w_{jk}^s the given score of j th criterion by k th (k=1,2, …, p) decision-maker. Then the following equation is used to normalize the scores and transform them to some values between zero and one.

$$w_{jk} = \frac{w_{jk}^s}{\sum_{j=1}^{m} w_{jk}^s} \tag{32}$$

where w_{jk} is the weight of j th criterion with respect to k th decision-maker, and $\sum_{j=1}^{m} w_{jk} = 1$.

Step 3. Obtain the performance values of alternatives with respect to each criterion and each decision-maker.The 9-point Likert scale is also used in this step for rating the performance of the alternatives. Here and subsequently, x_{ijk} stands for the performance value of i th alternative on j th criterion given by k th decision-maker.

Step 4. Define the stochastic multi-criteria decision-making problem according to the weights of criteria and performance values of alternatives elicited from decision-makers and the PERT distribution.Let w_j^a, w_j^b and w_j^c denote the minimum, most likely and maximum values of weights of each criterion in a PERT distribution, respectively. Also, x_{ij}^a, x_{ij}^b and x_{ij}^c show the minimum, most likely and maximum values of the performance values of alternative in a PERT distribution, respectively. Then the following equations are used to define the parameters of the PERT distributions of each element for simulation process of the decision-making problem.

$$w_j^a = \min_k w_{jk} \tag{33}$$

$$w_j^b = \frac{1}{p}\sum_{k=1}^{p} w_{jk} \tag{34}$$

$$w_j^c = \max_k w_{jk} \tag{35}$$

$$x_{ij}^a = \min_k x_{ijk} \tag{36}$$

$$x_{ij}^b = \frac{1}{p}\sum_{k=1}^{p} x_{ijk} \tag{37}$$

$$x_{ij}^c = \max_k x_{ijk} \tag{38}$$

Step 5. Start the Monte Carlo simulation process, set iteration counter to one (r=1) and define the number of iterations (N).In this step, four variables are defined to measure the ranking score of each alternative with respect to use of each MCDM method. We will denote by S_{izl} the score of i th alternative in z th rank (z=1,2, …,n) in l th MCDM method (l=1,2, …, L). In this study, we use four MCDM methods (L=4), and S_{iz1}, S_{iz2}, S_{iz3} and S_{iz4} show the ranking score variables related to the TOPSIS, COPRAS, WASPAS and EDAS, respectively. These variables are set to zero in this step (S_{izl}=0).

Step 6. Generate random values for the weights of criteria and performance values of alternatives according the PERT distribution (Eqs. (1) to (6)) and Eqs. (33)–(38).Let us denote by $w_j^{(r)}$ and $x_{ij}^{(r)}$ the randomly generated values of the weights of criteria and performance values of alternatives in r th iteration, respectively.

Step 7. Solve the randomly generated MCDM problem using all of the considered methods. In this study we use Eqs. (8)–(31) described in previous sections.

a) If i th alternative is placed in z th rank in l th MCDM method, increase the value of S_{izl} by one (S_{izl}=S_{izl}+1).
b) Increase the iteration counter by one (r=r+1).

Step 8. If the iteration counter is less than or equal to N ($r \le N$), go to Step 6, otherwise continue.

Step 9. Normalize the obtained ranking scores of different MCDM methods as follows:

$$S_{izl}^N = \frac{S_{izl}}{N} \tag{39}$$

Step 10. Calculate the aggregated ranking scores of the alternatives as follows:

$$S_{iz}^{AG} = \frac{1}{L}\sum_{l=1}^{L} S_{izl}^N \tag{40}$$

Step 11. Solve the following linear assignment model and find the optimal rank of alternatives:

$$Max\, f = \sum_{i=1}^{n}\sum_{z=1}^{n} S_{iz}^{AG} y_{iz}$$

subject to,

$$\begin{aligned} &\sum_{i=1}^{n} y_{iz} = 1 \quad \forall z \\ &\sum_{z=1}^{n} y_{iz} = 1 \quad \forall i \end{aligned} \tag{41}$$

where

$$y_{iz} = \begin{cases} 1 & \textit{if ith alternative is assigned to zth rank} \\ 0 & \textit{otherwise} \end{cases}$$

To clear the procedure, the flowchart of the proposed approach is also depicted in Fig. 2.

4. Application of the proposed approach

In this section, the proposed approach is applied to an example of evaluation of airline with multiple service quality criteria. For this aim, five airlines (alternatives) are considered for evaluation. To avoid advertising for these airlines, names of them are not called in this research, and we refer to them by A_1 to A_5.

According to the research of Chou et al. (2011) a questionnaire was designed with 28 sub-criteria (in five main criteria). The evaluation criteria and sub-criteria are presented in Table 1.

We contacted 32 travel agencies and got the email address of 186 tour leaders from them. These tour leaders worked for the travel agencies for more than a year. We sent an email to these tour leaders and requested them to cooperate with us in evaluation process if they have had some experience with the considered airlines. In the questionnaire, which sent by email, the participants were asked to score the importance of the evaluation sub-criteria and also the performance of each airline on each sub-criterion by using a 9-point Likert scale. During a month, we received some replies from 58 persons of the invited tour leaders. The received data are provided as supplementary material.

The 58 respondent of the questionnaire are considered as decision-makers of the problem to use the proposed approach for evaluation of the airlines. According to the steps 2 to 4 of the proposed approach, we determine the parameters of the PERT distributions for the normalized criteria weights and performance values of the alternatives. Tables 2 and 3 represent the parameters for criteria weights and performance values, respectively. It should be noted that the minimum, most likely and maximum values in these tables are calculated using Eqs. (33)–(38) and the data provided as supplementary material.

Using the values of Tables 2 and 3 we can go to the step 5 of the proposed approach and start the simulation process with any number of iterations (N). In this study, we run the proposed approach with different values of N to show the effect of this parameter on the final evaluation results. For this aim, the proposed approach is run with $N = 5, 10, 20, 50, 100, 500, 1000$ and 50000. By running the proposed approach the aggregated ranking scores are calculated. These values are shown in Table 4 for the defined numbers of iterations.

The effect of increasing the number of iterations on the normalized ranking scores of different MCDM methods and aggregated ranking scores for different ranks (z=1,2, …,5) depicted in Figs. 3–7.

According to these figures, the values of the aggregated ranking scores in different ranks (i.e. z = 1,2, …,5) are not stable at lower

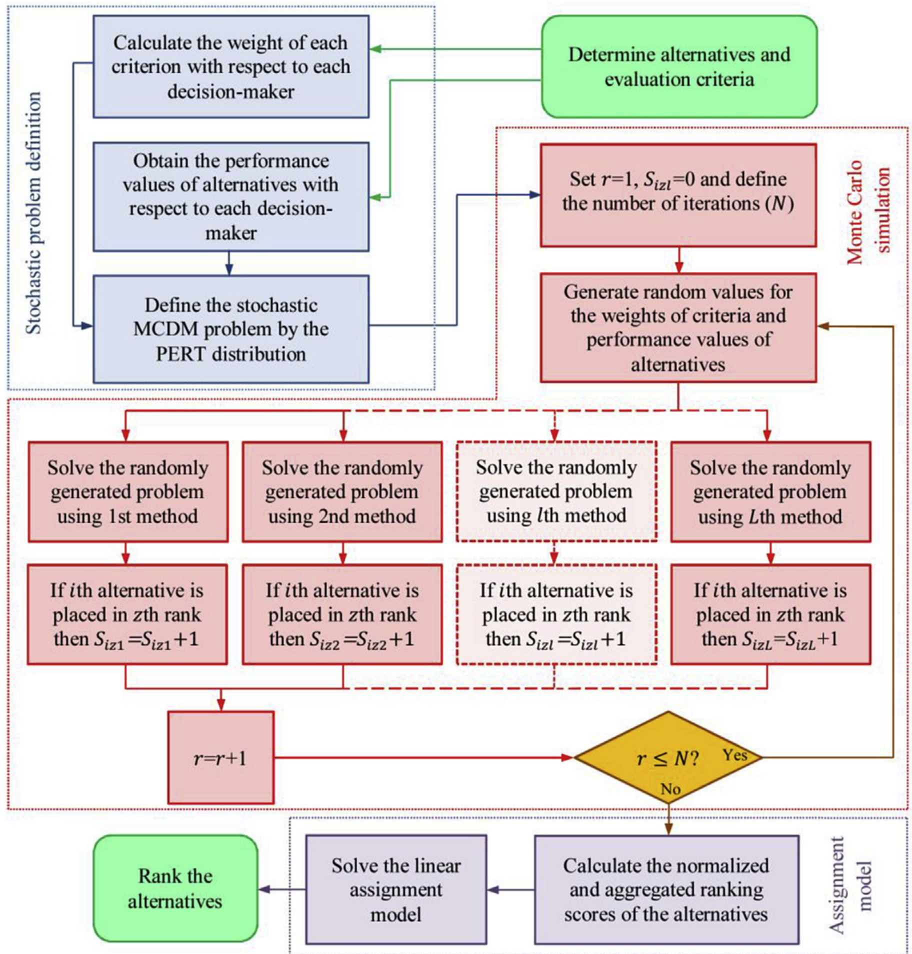

Fig. 2. The flowchart of the proposed approach.

Table 1
The service quality criteria for airline evaluation.

	Criteria		Sub-criteria
C_1	Tangibles	C_{11}	Comfort and cleanness of seat
		C_{12}	Quality of food and beverage
		C_{13}	In-flight newspapers, magazines and books
		C_{14}	In-flight washroom facility
		C_{15}	In-flight entertainment facilities and programs
		C_{16}	Availability of waiting lounges
		C_{17}	Size of airplane
C_2	Responsiveness	C_{21}	Courtesy of crew
		C_{22}	Handling of delay
		C_{23}	Efficient check-in/baggage handling services
		C_{24}	Crew's speed handling request
		C_{25}	Quality of the reservation services
		C_{26}	Crew's approach against unexpected situations
		C_{27}	Crew's willingness to help
		C_{28}	Appearance of crew
C_3	Reliability and assurance	C_{31}	Safety
		C_{32}	On-time departure and arrival
		C_{33}	Consistent ground/in-flight services
C_4	Empathy	C_{41}	Crew's behavior to delayed passenger
		C_{42}	Individual attention to passenger
		C_{43}	Understanding of passenger's specific needs
		C_{44}	Extent travel services
		C_{45}	Convenient ticketing process
		C_{46}	Customer complaint handling
C_5	Flight pattern	C_{51}	Flight problems
		C_{52}	Convenient flight schedules
		C_{53}	Frequency of flight
		C_{54}	Non-stop flight

Table 2
The PERT distribution parameters for criteria weights.

Criteria		w_j^a	w_j^b	w_j^c
C_1	C_{11}	0.0201	0.0465	0.0650
	C_{12}	0.0072	0.0226	0.0538
	C_{13}	0.0061	0.0166	0.0526
	C_{14}	0.0146	0.0367	0.0556
	C_{15}	0.0065	0.0223	0.0493
	C_{16}	0.0069	0.0222	0.0515
	C_{17}	0.0067	0.0228	0.0493
C_2	C_{21}	0.0140	0.0356	0.0588
	C_{22}	0.0207	0.0479	0.0629
	C_{23}	0.0064	0.0243	0.0504
	C_{24}	0.0208	0.0467	0.0629
	C_{25}	0.0211	0.0486	0.0643
	C_{26}	0.0140	0.0358	0.0588
	C_{27}	0.0069	0.0230	0.0496
	C_{28}	0.0135	0.0347	0.0630
C_3	C_{31}	0.0211	0.0535	0.0732
	C_{32}	0.0214	0.0555	0.0709
	C_{33}	0.0135	0.0359	0.0559
C_4	C_{41}	0.0066	0.0234	0.0504
	C_{42}	0.0140	0.0364	0.0584
	C_{43}	0.0064	0.0181	0.0461
	C_{44}	0.0063	0.0159	0.0490
	C_{45}	0.0203	0.0464	0.0643
	C_{46}	0.0196	0.0466	0.0602
C_5	C_{51}	0.0216	0.0473	0.0638
	C_{52}	0.0216	0.0457	0.0652
	C_{53}	0.0205	0.0514	0.0709
	C_{54}	0.0138	0.0375	0.0571
Sum		–	1	–

Table 3
The PERT distribution parameters for performance values of the alternatives.

	x_{ij}^a					x_{ij}^b					x_{ij}^c				
	A_1	A_2	A_3	A_4	A_5	A_1	A_2	A_3	A_4	A_5	A_1	A_2	A_3	A_4	A_5
C_{11}	4	2	3	3	1	6.8	5.0	7.6	7.5	3.2	9	8	9	9	7
C_{12}	3	1	3	1	1	7.8	3.1	6.8	2.6	3.1	9	6	9	7	7
C_{13}	2	1	3	1	3	4.8	3.2	6.8	3.4	7.4	8	7	9	6	9
C_{14}	1	1	3	1	3	3.5	2.2	6.7	3.1	7.8	7	7	9	7	9
C_{15}	4	2	3	3	1	6.8	4.7	6.8	7.4	2.4	9	8	9	9	7
C_{16}	3	2	2	1	1	6.9	5.1	5.2	2.2	3.3	9	8	8	7	7
C_{17}	2	1	3	3	1	5.1	3.0	7.7	7.6	2.2	8	7	9	9	7
C_{21}	2	3	3	1	1	5.2	7.1	6.4	3.3	1.9	8	9	9	7	7
C_{22}	3	1	3	1	2	7.7	3.0	6.6	3.6	5.1	9	7	9	7	8
C_{23}	1	1	2	1	3	3.2	2.4	5.0	3.4	6.2	7	7	8	7	9
C_{24}	1	1	2	1	3	2.0	3.1	5.0	3.5	6.9	7	7	8	7	9
C_{25}	1	2	2	2	4	1.8	5.0	3.4	4.7	6.9	7	8	7	8	9
C_{26}	1	3	1	1	2	3.5	8.0	2.2	3.6	4.9	7	9	7	7	8
C_{27}	1	3	3	2	1	2.2	6.6	7.9	5.0	3.8	7	9	9	8	7
C_{28}	3	3	3	1	1	6.8	6.6	7.9	2.4	3.5	9	9	9	7	7
C_{31}	3	1	2	1	3	7.6	3.2	4.9	2.4	6.7	9	7	8	7	9
C_{32}	3	2	2	1	3	6.7	3.4	5.0	2.1	8.2	9	7	8	7	9
C_{33}	3	1	1	1	2	6.7	2.5	3.3	3.4	5.1	9	7	7	7	8
C_{41}	3	1	1	2	1	7.8	3.5	3.3	4.9	2.1	9	7	7	8	7
C_{42}	1	1	4	1	2	3.2	2.7	6.6	2.2	4.9	7	7	9	7	8
C_{43}	1	2	1	1	1	1.9	5.1	3.5	3.6	2.3	7	8	7	7	7
C_{44}	2	1	3	1	1	5.0	2.3	6.9	3.2	3.5	8	7	9	7	7
C_{45}	2	1	1	3	1	5.0	3.2	3.3	6.6	2.4	8	7	7	9	7
C_{46}	3	1	2	1	2	6.4	3.6	5.2	3.6	4.9	9	7	8	7	8
C_{51}	3	3	2	3	1	6.7	6.7	5.0	7.7	3.1	9	9	8	9	7
C_{52}	3	1	3	1	1	7.4	2.3	6.4	2.8	3.1	9	7	9	7	7
C_{53}	1	1	2	1	3	2.2	3.2	5.1	2.3	6.4	7	7	7	7	9
C_{54}	4	1	2	1	1	6.8	3.2	5.0	3.5	2.2	8	7	8	7	7

Table 4
The aggregated ranking scores in different numbers of iterations.

N	z	S^{AG}_{1z}	S^{AG}_{2z}	S^{AG}_{3z}	S^{AG}_{4z}	S^{AG}_{5z}	N	z	S^{AG}_{1z}	S^{AG}_{2z}	S^{AG}_{3z}	S^{AG}_{4z}	S^{AG}_{5z}
5	1	0.600	0.000	0.250	0.000	0.150	100	1	0.420	0.000	0.523	0.000	0.058
	2	0.350	0.000	0.650	0.000	0.000		2	0.440	0.000	0.433	0.000	0.128
	3	0.050	0.150	0.100	0.000	0.700		3	0.140	0.030	0.045	0.070	0.715
	4	0.000	0.650	0.000	0.200	0.150		4	0.000	0.528	0.000	0.385	0.088
	5	0.000	0.200	0.000	0.800	0.000		5	0.000	0.443	0.000	0.545	0.013
10	1	0.450	0.000	0.250	0.000	0.300	500	1	0.380	0.000	0.574	0.000	0.047
	2	0.450	0.000	0.450	0.000	0.100		2	0.498	0.003	0.359	0.000	0.141
	3	0.100	0.000	0.300	0.000	0.600		3	0.120	0.036	0.067	0.018	0.760
	4	0.000	0.525	0.000	0.475	0.000		4	0.003	0.574	0.001	0.372	0.051
	5	0.000	0.475	0.000	0.525	0.000		5	0.000	0.388	0.000	0.611	0.002
20	1	0.488	0.000	0.488	0.000	0.025	1000	1	0.329	0.000	0.637	0.000	0.034
	2	0.463	0.000	0.425	0.000	0.113		2	0.572	0.002	0.321	0.000	0.105
	3	0.050	0.000	0.088	0.038	0.825		3	0.097	0.041	0.040	0.018	0.803
	4	0.000	0.700	0.000	0.300	0.000		4	0.002	0.567	0.002	0.377	0.052
	5	0.000	0.300	0.000	0.663	0.038		5	0.000	0.390	0.000	0.604	0.006
50	1	0.515	0.000	0.460	0.000	0.025	50000	1	0.340	0.000	0.620	0.000	0.040
	2	0.445	0.000	0.505	0.000	0.050		2	0.550	0.001	0.330	0.000	0.119
	3	0.040	0.015	0.035	0.010	0.900		3	0.108	0.039	0.049	0.021	0.782
	4	0.000	0.570	0.000	0.405	0.025		4	0.002	0.571	0.001	0.375	0.052
	5	0.000	0.415	0.000	0.585	0.000		5	0.000	0.389	0.000	0.604	0.007

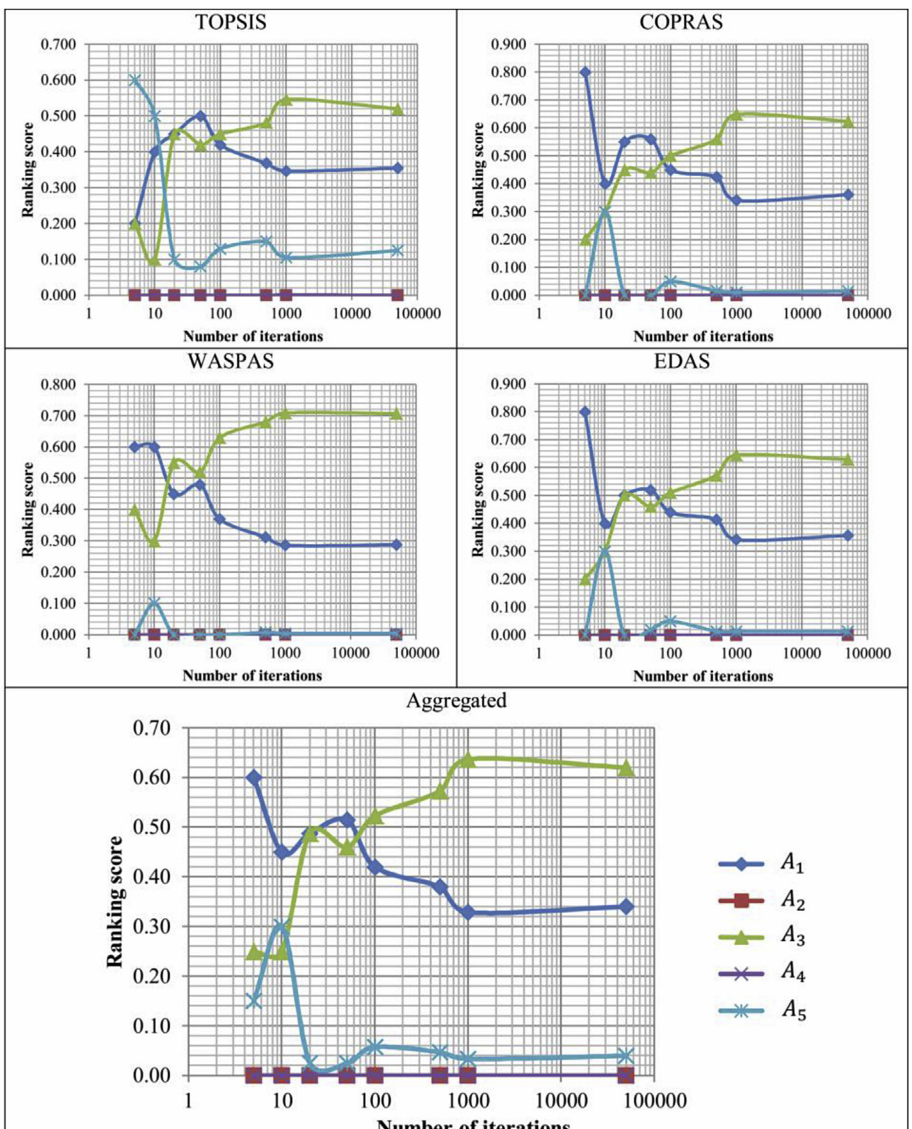

Fig. 3. Normalized and aggregated ranking scores in $z = 1$ and different values of N.

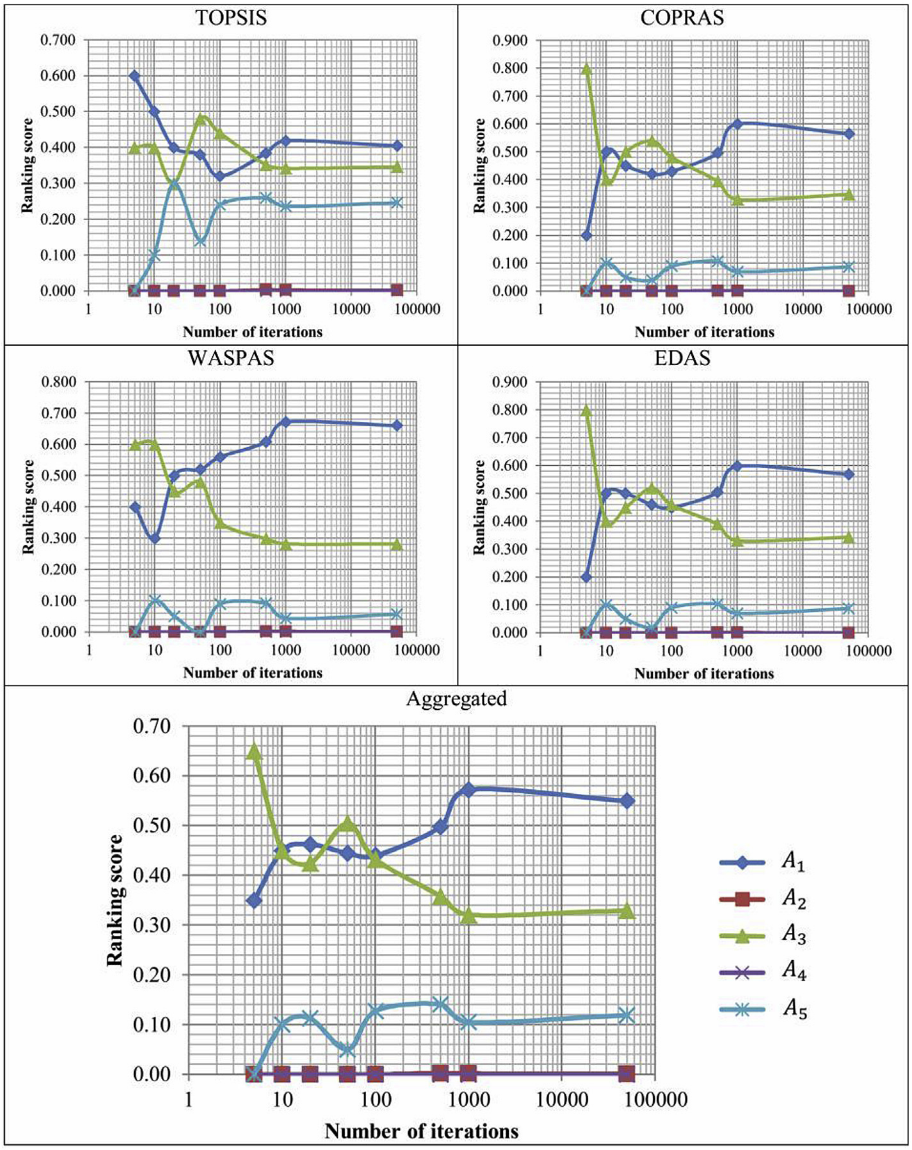

Fig. 4. Normalized and aggregated ranking scores in $z = 2$ and different values of N.

values of N, and the stability of these values increase when we run the proposed approach with higher number of iterations. This fact can also be seen in the normalized ranking scores of TOPSIS, COPRAS, WASPAS and EDAS. The instability of the ranking scores can lead to instability of final ranking of alternatives. However, in these figures we can see little variation in the ranking scores after $N = 1000$.

The linear assignment model which has been described in Step 11 of the proposed approach is used here to determine the final rank of the alternatives with different numbers of iterations. As an example, we formulate the assignment model for $N = 50000$ as follows:

$$Max\,f = 0.340y_{11} + 0.550y_{12} + 0.108y_{13} + 0.002y_{14} + 0.001y_{22} + 0.039y_{23} + 0.571y_{24} + 0.389y_{25} + 0.620y_{31} + 0.330y_{32} + 0.049y_{33} + 0.001y_{34} + 0.021y_{43} + 0.375y_{44} + 0.604y_{45} + 0.040y_{51} + 0.119y_{52} + 0.782y_{53} + 0.052y_{54} + 0.007y_{54}$$

subject to,

$$\sum_{i=1}^{5} y_{iz} = 1 \quad \forall z$$
$$\sum_{z=1}^{5} y_{iz} = 1 \quad \forall i$$
$$y_{iz} \in \{0, 1\}$$

The ranking results are presented in Table 5.

The effect of instability of ranking scores in lower number of iterations on the final ranking of the alternatives can be seen in Table 5. However, it can be said that the stable optimal rank of the alternatives is $A_3 > A_1 > A_5 > A_2 > A_4$. Therefore, we can say that A_3 is an airline that has the higher level of service quality than the other alternative airlines according to our evaluation based on the selected criteria of service quality. It should be noted that the simulation part of the proposed approach has been coded and run in MATLAB R2014a, and the linear assignment has been solved using LINGO Extended 16 (x64 Educational). All computations have been performed on a PC with 2.4 GHz CPU (Intel® Core™ i5-520M), 4 GB of RAM and Windows 7 (64 bit) operating system. The computational time of running the proposed approach with different number of iterations is presented in Fig. 8.

5. Discussion

The multi-criteria decision-making approaches have been used in many fields of science and engineering. However, there are still some issues to deal with MCDM problems with a group of decision-makers and validation of the evaluation results. In the case of group decision-making, when we are confronted with a few members in the group of decision-making, handling the problem is not difficult. For example, after quantifying their opinions, we can combine the opinions of them by using a simple average. On the other hand, if the number of members increases, the evaluation process will be more complex. In such situations, the opinions of the decision-makers, which are experts in many practical problems, may follow a distribution with some parameters which should be involved in the decision-making process. However, fitting different distributions and finding the best fit for the elicited data is a time-consuming problem because if there are m criteria and n alternatives we should find m distributions for importance (weights) of criteria and $m \times n$ distributions for performance values (elements of the decision-matrix). To deal with this problem, in this study, the PERT distribution, which is a flexible distribution, has been utilized for modelling decision-makers' opinions. This distribution uses the minimum, most likely and maximum parameters that can be very helpful to estimate opinions of decision-makers efficiently. It should be noted that the proposed approach can also be used in decision-making problems with small group of decision-makers.

To solve the MCDM problems, the values of criteria weights and performance values of alternatives should be specified first. The

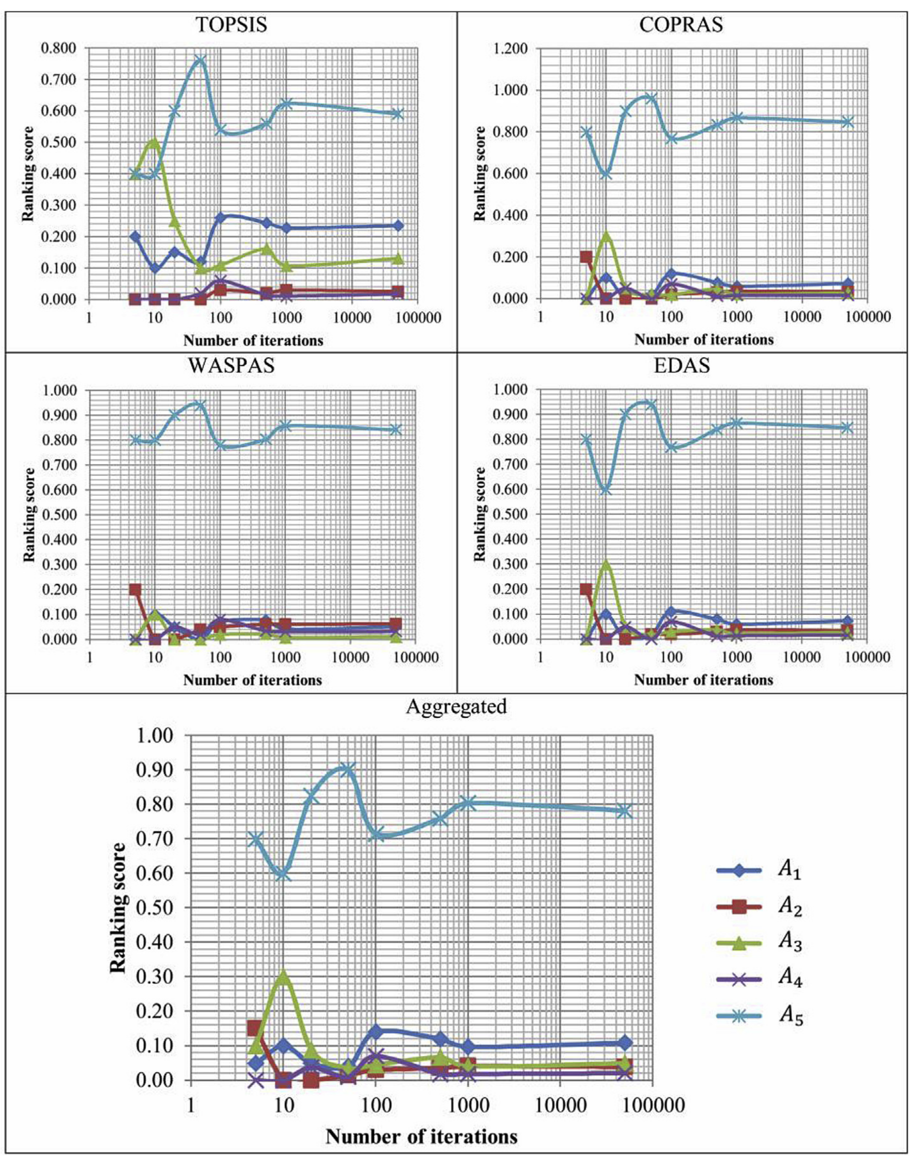

Fig. 5. Normalized and aggregated ranking scores in $z = 3$ and different values of N.

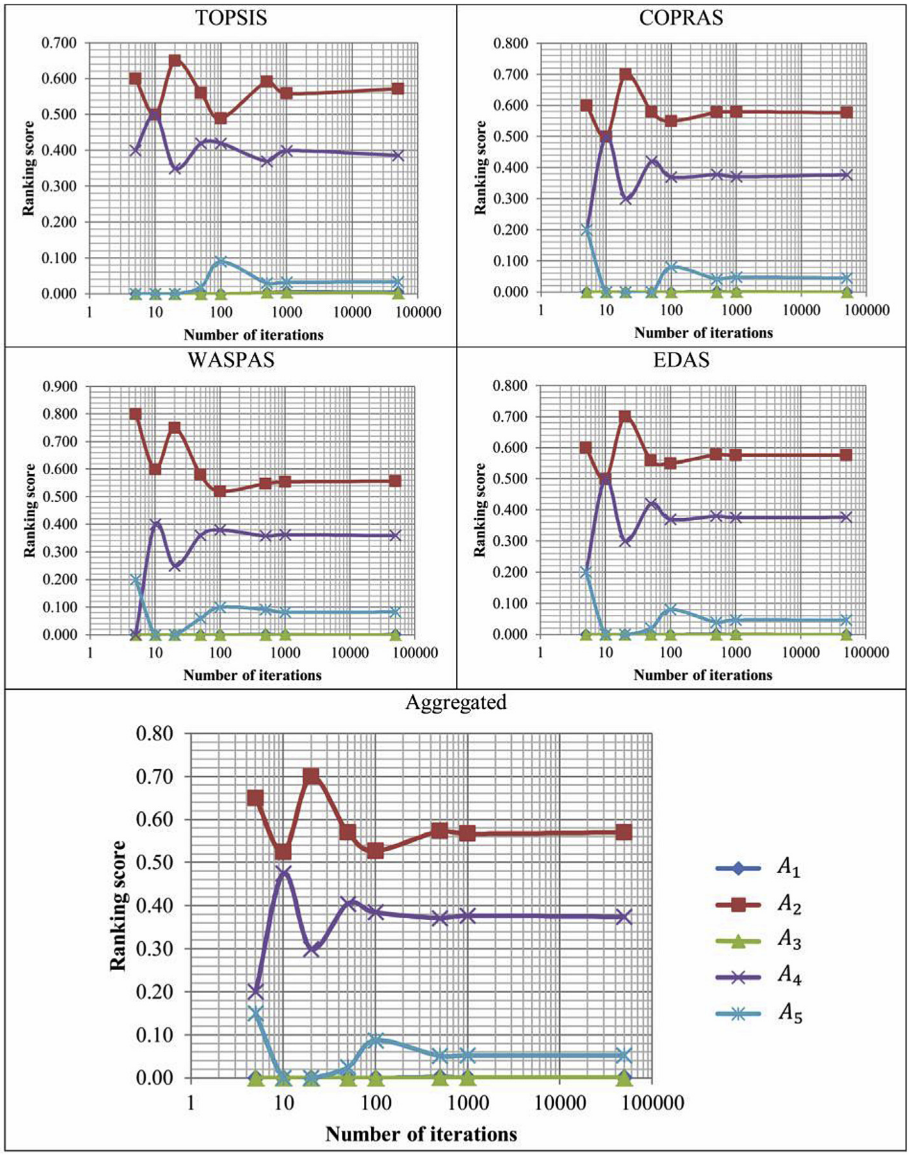

Fig. 6. Normalized and aggregated ranking scores in $z = 4$ and different values of N.

Monte Carlo simulation has been used in the proposed approach to generate random values for criteria weights and performance values of alternatives with respect to defined PERT distribution. Then the generated problems have been solved by four efficient MCDM methods.

One of the main issues in using MCDM approaches is the validation of ranking results. In most of the studies in this field, the ranking results are compared with the results of some existing MCDM approaches. As can be seen in the previous section, not only can the proposed approach yield a comparative analysis of the results of different MCDM methods, but also it gives a final ranking result based on an assignment model that involves the evaluation process of all the considered MCDM methods. Therefore, it can be said that the proposed approach helps us to reach a more accurate decision.

According to Fig. 8, we can say that the computational time of running the proposed approach has a relatively linear relation with the number of iteration, and the computational time in $N = 1000$ is about 20 s. Moreover, we have little variation in the ranking scores after $N = 1000$. Therefore, setting the number of iterations to 1000 can be appropriate to obtain reliable results for this problem.

Computational complexity of the proposed approach is depend on number of decision-makers, number of evaluation criteria, number of alternatives, number of MCDM methods used for evaluation and also level of complexity of each MCDM method.

6. Conclusion

In this study, we have proposed a new hybrid simulation-based assignment approach to handle decision-making problems with multiple criteria and a group of decision-makers. We have applied the proposed approach to a problem of evaluation airlines with multiple service quality criteria. The PERT distribution has been utilized to define a stochastic MCDM problem according to the opinions of decision-makers. Then a Monte Carlo simulation with four MCDM approaches including TOPSIS, COPRAS, WASPAS and EDAS has been designed to determine normalized and aggregated ranking scores of alternatives. We have use a linear assignment model to find the final rank of alternatives. The simulation process has been done in different numbers of iterations. The results shows

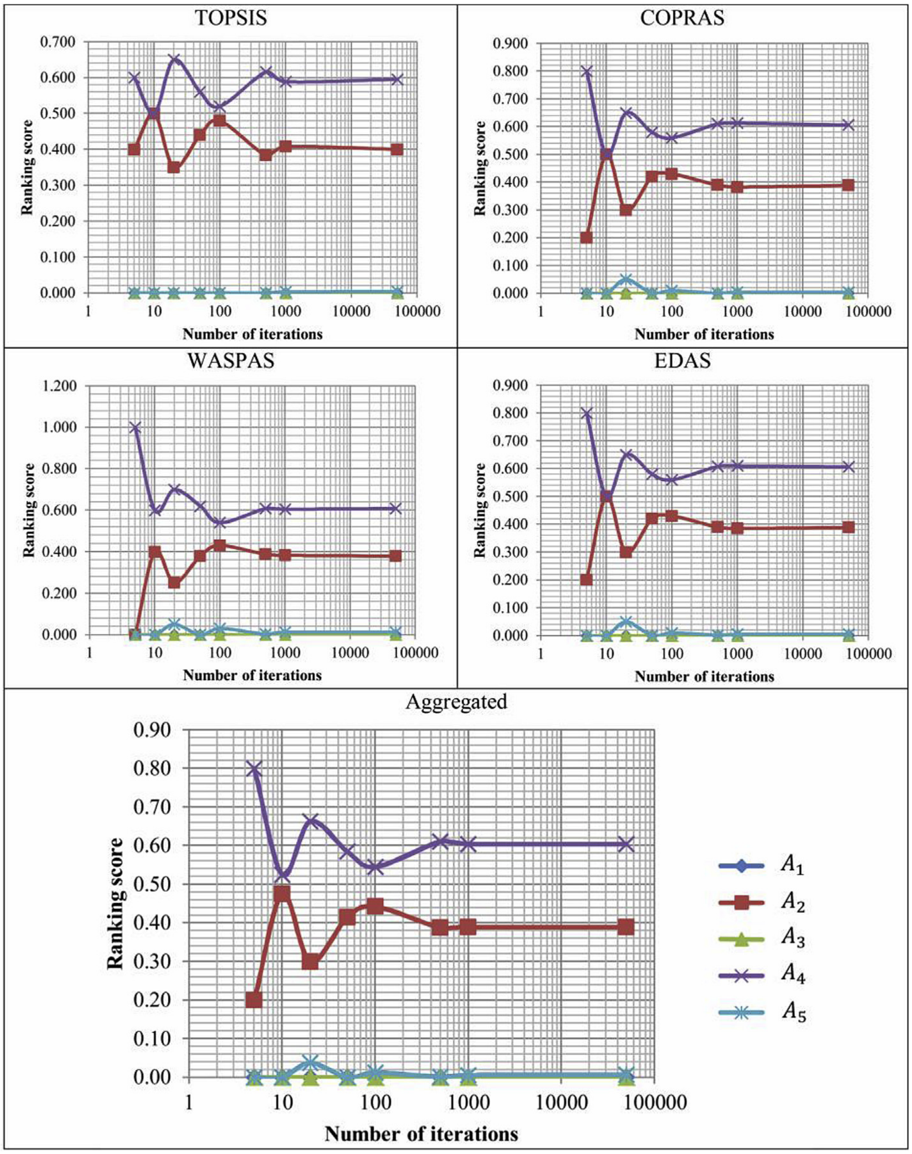

Fig. 7. Normalized and aggregated ranking scores in $z = 5$ and different values of N.

Table 5
The ranking results in different numbers of iterations.

Alternatives	N							
	5	10	20	50	100	500	1000	50000
A_1	1	1	2	1	2	2	2	2
A_2	4	4	4	4	4	4	4	4
A_3	2	2	1	2	1	1	1	1
A_4	5	5	5	5	5	5	5	5
A_5	3	3	3	3	3	3	3	3

that the normalized and aggregated ranking scores of alternatives will be more stable when we increase the number of iterations. This stability can be seen in the final ranking of the alternatives after solving the linear assignment model. Comparing the normalized ranking scores of different MCDM approaches with the aggregated values shows the stability and efficiency of the proposed approach. Although in the example of this study we have confronted with a situation that the normalized ranking scores of different MCDM methods and the aggregated ranking scores give the same ranking

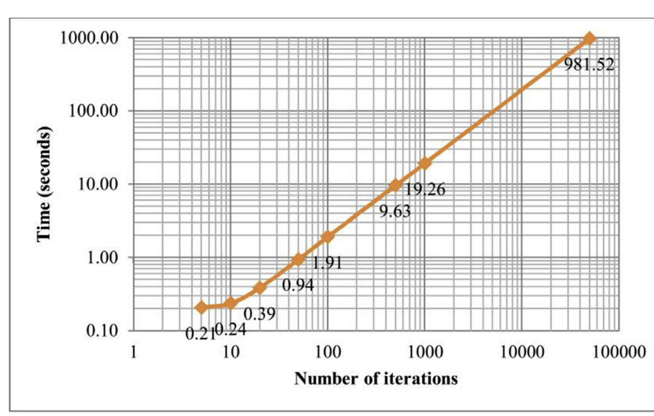

Fig. 8. The computational time of running the proposed approach.

results in the stable range, it can be different in other problems. Therefore, using the aggregated ranking scores can provide more reliable results than using individual MCDM methods. Overall, the proposed approach has two main advantages over the other decision-making approach. The first advantage of the proposed approach is its ability to involve opinions of a large number of decision-makers, and using multiple methods to increase the accuracy of evaluation process is the second advantage of it. However, because the proposed approach uses a Monte Carlo simulation, the computational time of running the process can increase when we are faced with a problem with a large number of alternatives and/or criteria.

As previously mentioned, although the TOPSIS, COPRAS, WASPAS and EDAS have been used in the algorithm of the hybrid proposed approach, the proposed approach is not limited to these methods. Accordingly, these methods can be replaced with any other efficient MCDM methods in future studies. Also, future research can incorporate another MCDM method like VIKOR, ARAS and MULTIMOORA into the algorithm to increase the comparability and accuracy of the results. Furthermore, the proposed approach can be applied to many other MCDM problems such as supplier selection, project selection, location selection and market segment evaluation.

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.jairtraman.2017.05.008.

References

An, M., Noh, Y., 2009. Airline customer satisfaction and loyalty: impact of in-flight service quality. Serv. Bus. 3 (3), 293–307.
Awasthi, A., Chauhan, S.S., Omrani, H., Panahi, A., 2011. A hybrid approach based on SERVQUAL and fuzzy TOPSIS for evaluating transportation service quality. Comput. Indus. Eng. 61 (3), 637–646.
Baker, D.M.A., 2013. Service quality and customer satisfaction in the airline industry: a comparison between legacy airlines and low-cost airlines. Am. J. Tour. Res. 2 (1), 67–77.
Beg, I., Rashid, T., 2013. TOPSIS for hesitant fuzzy linguistic term sets. Int. J. Intelligent Syst. 28 (12), 1162–1171.
Boran, F.E., Genç, S., Kurt, M., Akay, D., 2009. A multi-criteria intuitionistic fuzzy group decision making for supplier selection with TOPSIS method. Expert Syst. Appl. 36 (8), 11363–11368.
Bozorg-Haddad, O., Azarnivand, A., Hosseini-Moghari, S.-M., Loáiciga, H.A., 2016. WASPAS application and evolutionary algorithm benchmarking in optimal reservoir optimization problems. J. Water Resour. Plan. Manag. http://dx.doi.org/10.1061/(ASCE)WR.1943-5452.0000716.
Chakraborty, S., Zavadskas, E.K., Antucheviciene, J., 2015. Applications of waspas method as a multi-criteria decision-making tool. Econ. Comput. Econ. Cybern. Stud. Res. 49 (1), 5–22.
Chang, M., 2010. Monte Carlo Simulation for the Pharmaceutical Industry: Concepts, Algorithms, and Case Studies. CRC Press.
Chen, C.-F., 2008. Investigating structural relationships between service quality, perceived value, satisfaction, and behavioral intentions for air passengers: evidence from Taiwan. Transp. Res. Part A Policy Pract. 42 (4), 709–717.
Chen, C.-T., 2000. Extensions of the TOPSIS for group decision-making under fuzzy environment. Fuzzy Sets Syst. 114 (1), 1–9.
Chen, F.-Y., Chang, Y.-H., 2005. Examining airline service quality from a process perspective. J. Air Transp. Manag. 11 (2), 79–87.
Chen, I.S., 2016. A combined MCDM model based on DEMATEL and ANP for the selection of airline service quality improvement criteria: a study based on the Taiwanese airline industry. J. Air Transp. Manag. 57, 7–18.
Chen, S.-M., Lee, L.-W., 2010. Fuzzy multiple attributes group decision-making based on the interval type-2 TOPSIS method. Expert Syst. Appl. 37 (4), 2790–2798.
Chen, T.-Y., Tsao, C.-Y., 2008. The interval-valued fuzzy TOPSIS method and experimental analysis. Fuzzy Sets Syst. 159 (11), 1410–1428.
Choi, K., Lee, D., Olson, D.L., 2015. Service quality and productivity in the U.S. airline industry: a service quality-adjusted DEA model. Serv. Bus. 9 (1), 137–160.
Chou, C.-C., Liu, L.-J., Huang, S.-F., Yih, J.-M., Han, T.-C., 2011. An evaluation of airline service quality using the fuzzy weighted SERVQUAL method. Appl. Soft Comput. 11 (2), 2117–2128.
Das, M.C., Sarkar, B., Ray, S., 2012. A framework to measure relative performance of Indian technical institutions using integrated fuzzy AHP and COPRAS methodology. Socio-Economic Plan. Sci. 46 (3), 230–241.
Ghorshi Nezhad, M.R., Zolfani, S.H., Moztarzadeh, F., Zavadskas, E.K., Bahrami, M., 2015. Planning the priority of high tech industries based on SWARA-WASPAS methodology: the case of the nanotechnology industry in Iran. Ekon. istraživanja 28 (1), 1111–1137.
Gullco, R.S., Anderson, M., 2009. Use of the Beta distribution to determine well-log shale parameters. SPE Reserv. Eval. Eng. 12 (6), 929–942.
Hashemkhani Zolfani, S., Maknoon, R., Zavadskas, E.K., 2015. Multiple nash equilibriums and evaluation of strategies. New application of MCDM methods. J. Bus. Econ. Manag. 16 (2), 290–306.
Hwang, C.L., Yoon, K.P., 1981. Multiple Attribute Decision Making Methods and Applications: a State-of-the Art Survey. Springer London, Limited.
Ighravwe, D.E., Oke, S.A., 2016. A fuzzy-grey-weighted aggregate sum product assessment methodical approach for multi-criteria analysis of maintenance performance systems. Int. J. Syst. Assur Eng. Manag. http://dx.doi.org/10.1007/s13198-13016-10554-13198.
Jahanshahloo, G.R., Lotfi, F.H., Izadikhah, M., 2006. Extension of the TOPSIS method for decision-making problems with fuzzy data. Appl. Math. Comput. 181 (2), 1544–1551.
Kacprzyk, J., 1986. Group decision making with a fuzzy linguistic majority. Fuzzy Sets Syst. 18 (2), 105–118.
Kahraman, C., Keshavarz Ghorabaee, M., Zavadskas, E.K., Cevik Onar, S., Yazdani, M., Oztaysi, B., 2017. Intuitionistic fuzzy EDAS method: an application to solid waste disposal site selection. J. Environ. Eng. Landsc. Manag. 25 (1), 1–12.
Karabašević, D., Stanujkić, D., Urošević, S., Maksimović, M., 2016. An approach to personnel selection based on Swara and Waspas methods. Bizinfo (Blace) 7 (1), 1–11.
Keshavarz Ghorabaee, M., Amiri, M., Zavadskas, E.K., Turskis, Z., 2017. Multi-criteria group decision-making using an extended EDAS method with interval type-2 fuzzy sets. E&M Ekon. a Manag. 20 (1), 48–68.
Keshavarz Ghorabaee, M., Zavadskas, E.K., Amiri, M., Esmaeili, A., 2016a. Multi-criteria evaluation of green suppliers using an extended WASPAS method with interval type-2 fuzzy sets. J. Clean. Prod. 137, 213–229.
Keshavarz Ghorabaee, M., Zavadskas, E.K., Amiri, M., Turskis, Z., 2016b. Extended EDAS method for fuzzy multi-criteria decision-making: an application to supplier selection. Int. J. Comput. Commun. Control 11 (3), 358–371.
Keshavarz Ghorabaee, M., Zavadskas, E.K., Olfat, L., Turskis, Z., 2015. Multi-criteria inventory classification using a new method of evaluation based on distance from average solution (EDAS). Informatica 26 (3), 435–451.
Kuo, M.-S., 2011. A novel interval-valued fuzzy MCDM method for improving airlines' service quality in Chinese cross-strait airlines. Transp. Res. Part E: Logist. Transp. Rev. 47 (6), 1177–1193.
Liou, J.J.H., Chuang, Y.-C., Hsu, C.-C., 2016. Improving airline service quality based on rough set theory and flow graphs. J. Indus. Prod. Eng. 33 (2), 123–133.
Liou, J.J.H., Tsai, C.-Y., Lin, R.-H., Tzeng, G.-H., 2011. A modified VIKOR multiple-criteria decision method for improving domestic airlines service quality. J. Air Transp. Manag. 17 (2), 57–61.
Madić, M., Radovanović, M., Petković, D., Nedić, B., 2015. Selection of cutting inserts for aluminum alloys machining by using MCDM method. ACTA Univ. Cibiniensis 66 (1), 98–101.
Mardani, A., Jusoh, A., Md Nor, K., Khalifah, Z., Zakwan, N., Valipour, A., 2015a. Multiple criteria decision-making techniques and their applications – a review of the literature from 2000 to 2014. Econ. Research-Ekonomska Istraživanja 28 (1), 516–571.
Mardani, A., Jusoh, A., Zavadskas, E.K., 2015b. Fuzzy multiple criteria decision-making techniques and applications – two decades review from 1994 to 2014. Expert Syst. Appl. 42 (8), 4126–4148.
Mardani, A., Jusoh, A., Zavadskas, E.K., Kazemilari, M., Ungku, N.U.A., Khalifah, Z., 2016a. Application of multiple criteria decision making techniques in tourism and hospitality industry: a systematic review. Trans. Bus. Econ. 15 (1), 192–213.
Mardani, A., Jusoh, A., Zavadskas, E.K., Khalifah, Z., Nor, K.M.D., 2015c. Application of multiple-criteria decision-making techniques and approaches to evaluating of service quality: a systematic review of the literature. J. Bus. Econ. Manag. 16 (5), 1034–1068.
Mardani, A., Zavadskas, E.K., Khalifah, Z., Jusoh, A., Nor, K.M.D., 2016b. Multiple criteria decision-making techniques in transportation systems: a systematic review of the state of the art literature. Transport 31 (3), 359–385.
Mardani, A., Zavadskas, E.K., Streimikiene, D., Jusoh, A., Nor, K.M.D., Khoshnoudi, M., 2016c. Using fuzzy multiple criteria decision making approaches for evaluating energy saving technologies and solutions in five star hotels: a new hierarchical framework. Energy 117 (Part 1), 131–148.
Mousavi-Nasab, S.H., Sotoudeh-Anvari, A., 2017. A comprehensive MCDM-based approach using TOPSIS, COPRAS and DEA as an auxiliary tool for material selection problems. Mater. Des. 121, 237–253.
Mulliner, E., Malys, N., Maliene, V., 2016. Comparative analysis of MCDM methods for the assessment of sustainable housing affordability. Omega 59 (Part B), 146–156.
Mulliner, E., Smallbone, K., Maliene, V., 2013. An assessment of sustainable housing affordability using a multiple criteria decision making method. Omega 41 (2), 270–279.
Murray, N., 2004. Handbook on Import Risk Analysis for Animals and Animal Products: Quantitative risk assessment. World organisation for animal health.
Muturi, Jackline Sagwe, D., Namukasa, J., 2013. The influence of airline service quality on passenger satisfaction and loyalty: the case of Uganda airline industry. TQM J. 25 (5), 520–532.

Nguyen, H.-T., Md Dawal, S.Z., Nukman, Y., Aoyama, H., Case, K., 2015. An integrated approach of fuzzy linguistic preference based AHP and fuzzy COPRAS for machine tool evaluation. PLoS One 10 (9). http://dx.doi.org/10.1371/journal.pone.0133599.
Pakdil, F., Aydın, Ö., 2007. Expectations and perceptions in airline services: an analysis using weighted SERVQUAL scores. J. Air Transp. Manag. 13 (4), 229–237.
Parasuraman, A., Zeithaml, V.A., Berry, L.L., 1988. SERVQUAL: a multiple-item scale for measuring consumer perceptions of service quality. J. Retail. 64 (1), 12–40.
Park, J.-W., Robertson, R., Wu, C.-L., 2004. The effect of airline service quality on passengers' behavioural intentions: a Korean case study. J. Air Transp. Manag. 10 (6), 435–439.
Pavlovskis, M., Antucheviciene, J., Migilinskas, D., 2016. Application of MCDM and BIM for evaluation of asset redevelopment solutions. Stud. Inf. Control 25 (3), 293–302.
Peng, X., Liu, C., 2017. Algorithms for neutrosophic soft decision making based on EDAS, new similarity measure and level soft set. J. Intelligent Fuzzy Syst. 32, 955–968.
Rathi, K., Balamohan, S., 2016. A mathematical model for subjective evaluation of alternatives in fuzzy multi-criteria group decision making using COPRAS method. Int. J. Fuzzy Syst. http://dx.doi.org/10.1007/s40815-40016-40256-z.
Rust, R.T., Oliver, R.L., 1993. Service Quality: New Directions in Theory and Practice. Sage Publications.
Saha, G.C., Theingi, 2009. Service quality, satisfaction, and behavioural intentions: a study of low-cost airline carriers in Thailand. Man. Ser. Qual.: An Int. J. 19 (3), 350–372.
Stanujkic, D., Zavadskas, E.K., Keshavarz Ghorabaee, M., Turskis, Z., 2017. An extension of the EDAS method based on the use of interval grey numbers. Stud. Inf. Control 26 (1), 5–12.
Stefano, N.M., Filho, N.C., Vergara, L.G.L., Rocha, R.U.G.d., 2015. COPRAS (Complex Proportional Assessment): state of the art research and its applications. IEEE Lat. Am. Trans. 13 (12), 3899–3906.
Stević, Ž., Vasiljević, M., Vesković, S., 2016. Evaluation in logistics using combined AHP and EDAS method, XLIII international symposium on operational research, Serbia pp. 309–313.
Suki, N.M., 2014. Passenger satisfaction with airline service quality in Malaysia: a structural equation modeling approach. Res. Transp. Bus. Manag. 10, 26–32.
Tavana, M., Momeni, E., Rezaeiniya, N., Mirhedayatian, S.M., Rezaeiniya, H., 2013. A novel hybrid social media platform selection model using fuzzy ANP and COPRAS-G. Expert Syst. Appl. 40 (14), 5694–5702.
Thomopoulos, N.T., 2012. Essentials of Monte Carlo Simulation: Statistical Methods for Building Simulation Models. Springer Science & Business Media.
Tsaur, S.-H., Chang, T.-Y., Yen, C.-H., 2002. The evaluation of airline service quality by fuzzy MCDM. Tour. Manag. 23 (2), 107–115.
Turskis, Z., Juodagalvienė, B., 2016. A novel hybrid multi-criteria decision-making model to assess a stairs shape for dwelling houses. J. Civ. Eng. Manag. 22 (8), 1078–1087.
Turskis, Z., Zavadskas, E.K., Antucheviciene, J., Kosareva, N., 2015. A hybrid model based on fuzzy AHP and fuzzy WASPAS for construction site selection. Int. J. Comput. Commun. Control 10 (6), 113–128.
Vally, H., Glass, K., Ford, L., Hall, G., Kirk, M.D., Shadbolt, C., Veitch, M., Fullerton, K.E., Musto, J., Becker, N., 2014. Proportion of illness acquired by foodborne transmission for nine enteric pathogens in Australia: an expert elicitation. Foodborne pathogens Dis. 11 (9), 727–733.
Vose, D., 2008. Risk Analysis: a Quantitative Guide. John Wiley & Sons.
Wang, Y.-M., Elhag, T.M.S., 2006. Fuzzy TOPSIS method based on alpha level sets with an application to bridge risk assessment. Expert Syst. Appl. 31 (2), 309–319.
Xu, Z., Zhang, X., 2013. Hesitant fuzzy multi-attribute decision making based on TOPSIS with incomplete weight information. Knowledge-Based Syst. 52, 53–64.
Yazdani, M., Hashemkhani Zolfani, S., Zavadskas, E.K., 2016. New integration of MCDM methods and QFD in the selection of green suppliers. J. Bus. Econ. Manag. 17 (6), 1097–1113.
Ye, F., 2010. An extended TOPSIS method with interval-valued intuitionistic fuzzy numbers for virtual enterprise partner selection. Expert Syst. Appl. 37 (10), 7050–7055.
Zavadskas, E.K., Kaklauskas, A., Sarka, V., 1994. The new method of multicriteria complex proportional assessment of projects. Technol. Econ. Dev. Econ. 1 (3), 131–139.
Zavadskas, E.K., Mardani, A., Turskis, Z., Jusoh, A., Nor, K.M., 2016. Development of TOPSIS method to solve complicated decision-making problems: an overview on developments from 2000 to 2015. Int. J. Inf. Technol. Decis. Mak. 15 (3), 645–682.
Zavadskas, E.K., Turskis, Z., Antucheviciene, J., Zakarevicius, A., 2012. Optimization of weighted aggregated sum product assessment. Elektron. Ir. elektrotechnika 122 (6), 3–6.