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An integrated MCDM model for improving airline operational and financial performance

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ABSTRACT

The development of better methods for the improvement of airline performance is crucial, but this type of problem is difficult to solve because of the large number of complex factors involved making this inherently a multiple criteria decision making (MCDM) problem. In current studies, the factors to be evaluated are considered based upon a literature review or expert opinions. This study proposes an integrated model that combines data mining and MCDM to extract the critical factors for the improvement of airline performance. We apply the dominance-based rough set approach to extract the essential factors. The decision-making trial and evaluation laboratory method with the concepts of the analytic network process (DANP) is then used to construct the complex evaluation system. Finally, the VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje in Serbian, meaning multicriteria optimization and compromise solution) method is applied to select the suitable improvement alternative goals with the corresponding weights provided by the DANP method. The results show that the current model can be used as the basis for a benchmark industry improvement index which can be used to evaluate each airline individually with defined planning goals to achieve financial efficiency by improving operational efficiency.

1. Introduction

The past 10 years have seen large fluctuations and extreme changes in airline companies' financial and operational performance. The reasons for these are numerous, including problems caused by management and government regulators, as well as company mergers, restructuring and financial interventions and changes in the markets. For example, inappropriate financial and operational management decisions can affect internal costs, leading to chaotic high-risk situations, which if not dealt with appropriately could result in a declaration of bankruptcy or closing of the airline. Airline managers need a useful tool to identify, diagnose, and evaluate the company's financial and operational performance and rank goals for improvement. An airline's business performance depends upon customer service and internal operations to maximize financial efficiency. How to improve operational and financial performance and overcome problems is a particularly critical challenge for airline managers. The improvement of an airline's financial and operational performance involves a complex decision-making process requiring a systematic approach. Making such decisions entails dealing with a large number of conflicting criteria, which may not be clearly defined, as well as the consideration of interrelated criteria, mixing quantitative and qualitative criteria with subjective judgments (Gomes et al., 2014). All of these factors make airline performance improvement an inherently multiple criteria decision making (MCDM) problem. These multiple dimensions and criteria have motivated several scholars to search other fields to find advanced quantitative methods which can be adapted to create feasible approaches for performance optimization (Fethi and Pasiouras, 2010). Decisions for improving an airline's operational and financial performance, regardless of whether problems have been caused by external (e.g., fuel cost and consumption) or internal (e.g., net income) factors, are critical and unavoidable challenges which must be dealt with by management in order to survive in the air transportation industry. Any alterations in the criteria (factors) for operational efficiency can cause a number of reactions which impact financial efficiency especially because of the interrelationship between the criteria.

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Only a limited number of studies have appeared in the literature which are directly or indirectly related to airline efficiency (for examples see Lu et al., 2014; Lee and Worthington, 2014; Chang et al., 2014; Wu and Liao, 2014; Tavassoli et al., 2014; Arjomandi and Seufert, 2014; Chiu et al., 2013; Barros et al., 2013; Barros and Couto, 2013; Assaf and Josiassen, 2012; Delbari et al., 2016; Min and Joo, 2016; Duygun et al., 2016; Li et al., 2015b). Some have used statistical methods while others have applied data envelopment analysis (DEA) based models to deal with the problem. For example, Mallikarjun (2015) used network DEA (NDEA), Li et al. (2015a) used slack-based measure (SBM) DEA, and Tavassoli et al. (2014) combined the SBM and NDEA methods. The major limitation of previous studies has been that they have mainly focused on past quantitative data alone. Airline performance improvement is a complex system problem requiring qualitative judgements. However, depending upon qualitative analysis alone may provide overly superficial outcomes, while the results of quantitative analysis alone may easily lose their authenticity. A combination of these two approaches is needed to fully integrate various considerations, objectively based on the laws of science that would provide results with increased validity and reliability. The objective of this study is thus to produce an integrated model for improving airline performance that combines a data mining technique (quantitative data analysis) and multiple criteria decision-making (MCDM) models utilizing managers' qualitative judgements. Most MCDM models consider evaluating criteria derived from a literature review or expert opinions, opinions which might be subjective due to the vagueness of human judgments and preferences. Different experts will also generate different evaluation criteria. In today's big data era, interest in systematically exploring historical data with different methods to find new information has been increasing worldwide. Data mining techniques can be combined with MCDM methods to provide an excellent platform for such exploration, in this case, combining the factors to generate acceptable solutions. Thus, data mining techniques are used to extract objective evaluation criteria and the MCDM method is used to provide directions for improvement for airlines.

The integrated MCDM model proposed in this paper is divided into four stages: (1) the dominance-based rough set approach (DRSA) is used to identify the critical criteria in each dimension; (2) an evaluation system is constructed with the decision-making trial and evaluation laboratory (DEMATEL) method; (3) the influential weights of the criteria are analyzed through a DEMATEL-based analytic network process (DANP) method; and (4) the optimal airline performance and improvement goals for airlines are identified and ranked using VIKOR (i.e., VlseKriterijumska Optimizacija I Kompromisno Resenje in Serbian, meaning multicriteria optimization and compromise solution). The proposed model is capable of a facilitating the financial and operational improvement decision-making process and minimizing possible biases during the ranking and goal improvement prioritizing process for each airline. The usefulness and effectiveness of the proposed method is demonstrated in an empirical example, using 10 years of historical data provided by the Office of the Assistant Secretary for Research and Technology of the US Department of Transportation. This integrated model for operational and financial performance improvement can assist airline management to (1) understand the systematic influential network relation structure among the criteria, (2) find the essential factors and priorities in all dimensions, (3) select the most critical financial and operational performance factors with precision in a short period of time, and (4) improve the performance of the financial and operational dimensions by ranking and benchmarking the best practices. The empirical example demonstrates that this managerial tool can facilitate the decision-making process and the benchmarking ranking accurately, minimizing the time required and consequently reducing the costs involved in bad decision-making. The method and the final ranking table may be adapted to multiple cases, thereby helping airlines to improve their decision-making ability. Thus, companies can enhance the use of their resources and improve their financial and operational performance. Managers can pay more attention to the customer service by controlling the operational dimensions, minimizing the financial negative effects of critical operations mismanagement, and consequently, enhancing their overall competitiveness.

Prior works related to financial and operational performance in the airline industry have been mainly relied upon quantitative data and DEA models. However, airline performance improvement involves complex factors and needs managers' qualitative judgement. The evaluating systems constructed with traditional MCDM models might be too subjective due to the uncertainty of expert opinions. This study contributes to the literature by providing an integrated model that can objectively extract the essential criteria which can then be used to build an evaluation system that also consider managers' qualitative judgements, with the aim of improving airline performance. The remainder of this paper is structured as follows: Section 2 offers a brief review of the existing literature related to this topic. Section 3 describes the proposed decision rule-based soft computing model. Section 4 demonstrates the effectiveness of this proposed decision rule-based soft computing model by evaluating 10 years of historical data for the US airline industry. Section 5 presents some conclusions and closing remarks.

2. Literature review

Over the past decades, various methods have been proposed to address airline performance problems. These can be categorized into two major types of approaches: (1) DEA and mathematical programming models, and (2) MCDM approaches.

2.1. DEA and mathematical programming models

DEA and network DEA models have been used in a number of studies related to the operating and financial efficiency approaches for airlines. Lu et al. (2014) used a two-stage network DEA method to examine production and marketing efficiency in 30 US airlines. Lee and Worthington (2014) performed DEA and simultaneously estimated scores with a bootstrapped truncated regression model to explain the efficiency drivers for 42 US and European airlines. A virtual frontier network SBM was proposed by Li et al. (2015a) to evaluate the efficiency of 22 airlines from 2008 to 2012. Chang et al. (2014) analyzed trade-offs between labor and capital measures among 27 international airlines. The DEA results reported that fuel consumption and revenue structure are the major causes of inefficiency in airlines.

Arjomandi and Seufert (2014) applied a bootstrapped DEA method to evaluate performance among 48 international airlines finding that low-cost carriers are operating under increasing returns to scale. Choi et al. (2015) analyzed 12 US airlines. They evaluated service quality as a factor related to service productivity by applying a service quality-adjusted DEA and Mann–Whitney test to illustrate the tradeoff between quality and productivity. Barros et al. (2013) proposed a B-convex model which data from 10 US airlines to prove that airline efficiency is influenced by the size of the airline, mergers, and acquisitions. Barros and Couto (2013) applied the Luenberger productivity index and Malmquist productivity index as they reported on the managerial causes of technical efficiency and the variations in strategies adopted by 23 European airlines. Moreover, Mallikarjun (2015) developed an unoriented DEA network method to measure the performance of

US airlines and identify the sources of inefficiency. Chou et al. (2016) developed an airline performance evaluation model, called the metadynamic network SBM, which incorporated the concept of metafrontiers to facilitate comparisons of the performance of decision-making units, while simultaneously generalizing the SBM, network SBM, and dynamic SBM.

2.2. MCDM approaches

The use of MCDM approaches for airline industry applications has been discussed by many authors. For example Hsu and Liou (2013) combining the Decision Making Trial and Evaluation Laboratory and the Analytical Network Process (DANP) methods to solve an outsourcing provider decision problem for the airline industry. Li et al. (2017) proposed a hybrid approach based on a fuzzy analytic hierarchical process (AHP) and the 2-tuple fuzzy linguistic method for the evaluation of in-flight service quality, and conducted an application to study the comprehensive performance of in-flight service quality in three Chinese airlines. Delbari et al. (2016) used Delphi and AHP techniques to investigate the key competitiveness indicators and drivers of full-service airlines. Garg (2016) developed a robust hybrid decision model for the evaluation and selection of strategic alliance partners in the airline industry, applying an AHP for evaluation of the criteria and the fuzzy technique for order performance by similarity to ideal solution (FTOPSIS) for the selection of a strategic alliance partner, demonstrating the applicability of their technique in a case for an Indian airline. Chen (2016) proposed a combined MCDM model based on DEMATEL and ANP for the selection of airline service quality improvement criteria, basing this study on the Taiwanese airline industry. Lupo (2015) considered the application of a fuzzy extension of the ServPerf service conceptual model to estimate quality scores for fundamental service criteria. The non-compensative multi-criteria decision-making ELECTRE III method was employed to point out the quality ranking of service alternatives in a comparative evaluation of the service quality of international airports in Sicily. Additionally, Lin and Huang (2015) used ANP to measure the determinants of low cost carriers purchase intentions and performed a comparison of potential and current customers. Chao and Kao (2015) proposed a method for the selection of a strategic cargo alliance by airlines using the Fuzzy Delphi Method (FDM) and calculating the weights of the selected dimensions and criteria using the Fuzzy Analytic Hierarchy Process (FAHP).

Few articles have discussed the application of the MCDM method to airline performance. Barrosa and Wanke (2015) applied a two-stage TOPSIS and neural network approach to analyze the efficiency of African airlines. The results revealed that network size-related variables, such as economies of scale, are most crucial for explaining efficiency levels in the African airline industry; however, the impact of fleet mix and public ownership could not be neglected. Wang (2008) applied gray relational analysis to cluster financial ratios and find representative indicators. The author also applied a fuzzy MCDM (FMCDM) method to evaluate the financial performance of domestic airlines in Taiwan. Their results revealed that the financial performance of these airlines could easily be evaluated using the FMCDM method, regardless of the number of alternatives and the location of financial competition in the airline market.

There are some limitations to studies found in the literature. Because both mathematical programming and DEA methods are extreme point techniques, noise such as measurement error can cause considerable problems. In addition, although DEA estimates the "relative" efficiency it very narrowly converges to the "absolute" efficiency. In other words, it can find how well a company is performing in comparison to its peers but not compared with "the best or ideal theoretical scenario." Furthermore, the statistical hypothesis tests involved in DEA are difficult because this method is nonparametric. The MCDM models are more flexible tools enabling the combination of quantitative and qualitative characteristics, for considering the interrelationship among criteria and weighting the priorities for the best decisions by considering the weight of each involved criterion. However, in this method, the derivation of the assessing criteria or factors usually remains questionable, because of the lack of an objective evaluation method. Thus, this study applies DRSA, based on the rough set theory (Pawlak, 1982), to extract the most essential factors relative to airline performance. The MCDM methods are then used to investigate the weight of the criteria and conduct gap analysis for improvement. The proposed models are discussed in the next section. See Table 1 for a summary of the afore-mentioned literature.

3. The proposed hybrid MCDM model

A decision-making process involves the interaction of several factors in logical order, starting with the main goal, which is to finally choose the best alternative, according to the established criteria. In this study, the DRSA method is used to derive the essential criteria based on historical data obtained from the Office of the Assistant Secretary for Research and Technology, part of the United States Department of Transportation. The DRSA is a data mining technique that can generate a set of decision rules. Based on the decision rules, we can extract the essential criteria that are more closely correlated to airline performance. The essential criteria decided on by the DRSA are then refined by the experts' opinions. The DEMATEL method is then applied to build a relation structure among the criteria for airline performance improvement. When the relationships between criteria are decided, the DANP method can be applied to derive the influential weights for each criterion. Finally, the VIKOR method can be used to analyze the gap to the aspired to ideal level, based on the influential weights for each airline. The procedure is illustrated in Fig. 1.

3.1. DRSA method

The DRSA is an effective data mining technique that can analyze both quantitative and quantitative data with preferences. The DRSA starts with an information table or information system that can be represented with "objects" placed in rows and "attributes" in columns. The ordinal evaluation of objects and criteria/attributes is the main difference between DRSA compared with classical rough set theory. The typical DRSA data table is comprised of four tuples, which can be identified as an information system (IS) for $IS = (U, Q, V, f)$, where U is a finite universe set; Q is a finite set of k attributes (i.e., $Q = \{q_1, q_2 \ldots, q_k\}$); V is the value domain of the attribute (i.e., $V = \cup_{q \in Q} V_q$); and f denotes a total function (i.e., $f : U \times Q \rightarrow V$). The attributes in a typical DRSA model are comprised of condition attribute H and decision attribute E, and the conditional attributes are often regarded as the criteria for an MCDM evaluation problem.

Suppose that there are n objects in U. A complete outranking relation on U can be defined as $\succ_q$ with respect to a criterion $q \in Q$. If $x \prec_q y$ for $x, y \in U$, then it denotes that "x is at least as good as y with respect to criterion q". In DRSA, the outranking relation $\succ_q$ is generally supposed to be a completely preordered relation with respect to criterion q. Decision attribute $q \in E$ divides U into a finite number of decision classes (such as m decision classes), i.e., $Cl = \{Cl_t : Cl_1, Cl_2, \ldots, Cl_m\}$ for $t = 1, 2, \ldots, m$. For each $x \in U$, object x belongs to only one class $Cl_t (Cl_t \in Cl)$. Assuming that Cl has preferential order (i.e., for all $r, s = 1, \ldots, m$, if $r \succ s$, the decision class Cl_r is preferred to Cl_s), a downward union $Cl_t^{\lesssim}$ and an upward union $Cl_t^{\gtrsim}$ of the classes can be defined by Eqs. (1) and (2):

Table 1
Summary table of the mentioned literature.

Author	Aims	Criteria	Method	Results
Lu et al. (2014)	Examined 30 US airlines'	Production and marketing efficiency	Two-stage network DEA	Allows the performance measurement process to be assessed, thus, providing a new direction for measuring airline performance.
Lee and Worthington (2014)	Simultaneously estimated scores for 42 US and European airlines	Airline efficiency drivers	DEA and bootstrapped truncated regression model	US and most major European airlines need to scale-down operations.
Li et al. (2015a)	Evaluated the efficiency of 22 airlines from 2008 to 2012.	Airline efficiency drivers	Virtual frontier network SBM	The new model can be applied to a new benchmark airline such as Scandinavian Airlines. Although passenger traffic, cargo traffic and revenue decreased from 2008 to 2009, the overall efficiency of most airlines increased in that period.
Chang et al. (2014)	Analyzed trade-offs between labor and capital measures among 27 international airlines	Labor and capital	DEA	Fuel consumption and revenue structure are the major causes of inefficiency in airlines.
Arjomandi and Seufert (2014)	Evaluated performance of 48 international airlines	Environmental performers	Bootstrapped DEA	European full-service carriers (FSCs) seem relatively more environmentally efficient. Many of the most technically efficient carriers are from China and North Asia. Low-cost carriers (LCCs) are found to be more environmentally oriented than FSCs. Low-cost carriers are operating under increasing returns to scale.
Choi et al. (2015)	Evaluated the service quality of 12 US airlines	Service productivity	Service quality-adjusted DEA, and Mann–Whitney test	Low-cost airlines were found to benefit by marginal improvements in service, often unexpected by their clientele. Network carriers, however, tended to have a harder time meeting service expectations. While there were short-term tradeoffs between service quality and productivity, in the long term, a focus on service quality may help increase customer satisfaction, thus improving service productivity and overall organizational performance.
Barros et al. (2013)	Examined data for 10 US airlines to prove airline efficiency	Size of the airline, mergers, and acquisitions	B-convex model	US airline efficiency can be influenced by the size of the airline, mergers and acquisitions, and by time. Policy implications are derived.
Barros and Couto (2013)	Reported on the managerial causes of technical efficiency and the variations in the strategies adopted by 23 European airlines.	Efficiency and variations in strategies	Luenberger productivity index and Malmquist productivity index.	Productivity decreased for almost all airlines between 2000 and 2011. Productivity rose for a small group that includes the low cost airlines in the sample.
Mallikarjun (2015)	Measured the performance of US airlines and identified the sources of its inefficiency	Performance and efficiency	Unoriented DEA network	The results provide an insight into process-specific improvements for airline operational managers.
Chou et al. (2016)	Developed an airline performance evaluation model	Performance of decision-making units	Metadynamic network SBM	Suggested the airlines should put more focus on input resource reduction for productivity improvement.
Hsu and Liou (2013)	Solved an outsourcing provider decision for the airline industry.	Airline outsourcing	Decision Making Trial and Evaluation Laboratory and the Analytical Network Process (DANP)	Employees with good knowledge skills contribute to better service quality; a good relationship between airlines and their partners is the foundation of a successful outsourcing activity; risk plays a major role in the outsourcing evaluation system, and has the greatest effect on the other dimensions.
Li et al. (2017),	Evaluation of in-flight service quality	Comprehensive examination of in-flight service quality for three airlines in China.	Fuzzy AHP and 2-tuple fuzzy linguistic method	The key factors affecting in-flight service quality were identified.
Delbari et al. (2016)	Investigated the key indicators and drivers of competitiveness indicators for full-service airlines.	Key competitiveness drivers.	Delphi and AHP	The ranking of the key competitiveness drivers with respect to each indicator differs significantly. The findings of this research provide important implications for the evaluation and improvement of the competitiveness of full-service airlines.
Garg (2016)	Selection of strategic alliance partners and demonstrated the applicability of this method in a case study of an Indian airline.	Integration & Network, Marketing & Service, and Logistics & Resources	Analytic hierarchy process (AHP) and fuzzy technique for order performance by similarity to ideal solution (FTOPSIS).	Considered the vagueness/impreciseness of expert opinions in the evaluation process which makes this method a powerful tool in the multi criteria decision making process
Chen (2016)	Selection of airline service quality improvement criteria based on the Taiwanese airline industry.	Safety, Service, Satisfaction and Management.	Combined MCDM model based on DEMATEL and ANP.	Found the most important service quality improvement criteria for Taiwanese airlines.
Lupo (2015)	Pointed out the quality ranking of service alternatives in a study	Quality of service alternatives.	Fuzzy extension of the ServPerf and ELECTRE III method	Only a few key service aspects played a focal role in airport service quality.

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Table 1 (*continued*)

Author	Aims	Criteria	Method	Results
	that compared and evaluated the service quality of international airports in Sicily.			
Lin and Huang (2015)	Measured the determinants of low cost carriers purchase intentions and performed a comparison of potential and current customers.	Generated criteria that affect customer intentions to purchase LCCs.	Analytic network process (ANP)	Both potential and current customers considered reliability and image to be the most important criteria.
Chao and Kao (2015)	Selection of strategic cargo alliances by airlines.	Cargo business benefit	Fuzzy Delphi Method (FDM) and Fuzzy Analytic Hierarchy Process (FAHP).	China Airlines achieved greater benefits by choosing SkyTeam Cargo rather than WOW. Provided airlines with a useful reference for future strategic cargo alliance selection. Business benefit is the most important dimension for airlines selecting a cargo alliance.
Barrosa and Wanke (2015)	Analyzed the efficiency of African airlines	Airline efficiency Factors.	Two-stage TOPSIS and neural network approaches.	The network size-related variables, such as economies of scale, are most crucial for explaining efficiency levels in the African airline industry. However, the impact of fleet mix and public ownership cannot be neglected.
Wang (2008)	Evaluated the financial performance of domestic airlines in Taiwan.	Financial Factors.	Gray relation analysis and fuzzy MCDM (FMCDM)	The financial performance of these airlines can easily be evaluated using the FMCDM method, regardless of the number of alternatives and the location of finance competition in the airline market.

$$\mathrm{Cl}_t^{\leqq} = \bigcup_{s \le t} \mathrm{Cl}_s; \tag{1}$$

$$\mathrm{Cl}_t^{\geqq} = \bigcup_{s \ge t} \mathrm{Cl}_s. \tag{2}$$

The condition attributes (criteria) can be used to classify decision classes by their dominance relations. Given a set of attributes $F \subseteq H$ and $x, y \in U$, x dominates y with respect to a set of attributes F which could be denoted by $x\mathrm{D_F}y$ to represent that x F-dominates y. Therefore, a set of objects (instances) dominating x is termed an F-dominating set as in Eq. (3), and a set of objects dominated by x is called an F-dominated set as in Eq. (4):

$$\mathrm{D}_F^+(x) = \{y \in U : y\mathrm{D}_F x\}; \tag{3}$$

$$\mathrm{D}_F^-(x) = \{y \in U : x\mathrm{D}_F y\}. \tag{4}$$

The F-dominating set and F-dominated set can be used to represent a collection of upward and downward unions of decision classes, which may represent granules of knowledge. The F-lower, defined by Eq. (5), and F-upper approximation of an upward union with respect to $F \subseteq H$ can be defined as in Eq. (6):

$$\underline{F}\left(\mathrm{Cl}_t^{\geqq}\right) = \left\{x \in U : E_F^+(x) \subseteq \mathrm{Cl}_t^{\geqq}\right\}; \tag{5}$$

$$\overline{F}\left(\mathrm{Cl}_t^{\geqq}\right) = \left\{x \in U : E_F^- \cap \mathrm{Cl}_t^{\geqq} \neq \varnothing\right\}. \tag{6}$$

The F-lower approximation $\underline{F}(\mathrm{Cl}_t^{\geqq})$ denotes all of the objects in $x \in U$ that are sure to be included in the upward union $\mathrm{Cl}_t^{\geqq}$, whereas all objects have at least the same or better evaluation with regard to all criteria $F \subseteq H$. With the F-upper approximation and F-lower approximation of $\mathrm{Cl}_t^{\geqq}$, the F-boundary of $\mathrm{Cl}_t^{\geqq}$ is defined as:

$$Bn_F = \overline{F}\left(\mathrm{Cl}_t^{\geqq}\right) - \underline{F}\left(\mathrm{Cl}_t^{\geqq}\right). \tag{7}$$

The so-called dominance principle requires that if object x dominates object y on all considered criteria $F \subseteq H$ (i.e., in the conditional part), then object x should also dominate y in the decision attribute. The objects that comply with the dominance principle are called consistent; otherwise, they are inconsistent. Moreover, the quality of approximation is defined as the ratio expressed in Eq. (8). Ratio $\gamma_F(\mathrm{C}l)$ can be regarded as a consistency ratio for all the objects from U and all considered condition attributes $F \subseteq H$.

$$\gamma_F(\mathrm{C}l) = \frac{\left|U - \left(\bigcup_{t \in \{2,\dots,n\}} Bn_F\left(\mathrm{Cl}_t^{\geqq}\right)\right)\right|}{|U|}. \tag{8}$$

Furthermore, the accuracy of approximation of the ordered classes $\mathrm{Cl}_t^{\geqq}$ with regard to a set of criteria $F \subseteq H$ is defined as $\alpha_F(\mathrm{Cl}_t^{\geqq})$ in Eq. (9), and $|\cdot|$ in Eqs. (8) and (9) is the cardinality of a set.

$$\alpha_F\left(\mathrm{Cl}_t^{\geqq}\right) = \frac{\left|\underline{F}\left(\mathrm{Cl}_t^{\geqq}\right)\right|}{\left|\overline{F}\left(\mathrm{Cl}_t^{\geqq}\right)\right|}. \tag{9}$$

Each minimal subset $F \subseteq H$ that may satisfy $\gamma_F(\mathrm{C}l) = \gamma_H(\mathrm{C}l)$ is called a REDUCT of $\mathrm{C}l$, and the intersections of all REDUCTs represent the indispensable attributes to maintain the quality of the approximation, called $\mathrm{CORE}_{\mathrm{C}l}$. The DRSA decision rules comprise two types: certain and possible. The certain decision rules provide conditions for objects belonging to $\underline{F}(\mathrm{Cl}_t^{\geqq})$. More details for DRSA can be found in Greco et al. (2001, 2002) and Błaszczyński et al. (2007, 2013). In this paper, the strength of the rules is used to select the relevant criteria.

3.2. The DEMATEL method

The DEMATEL methodology can reflect the relationship between the causes and effects of the criteria in an intelligent structural model. The final product of this method is a graphic

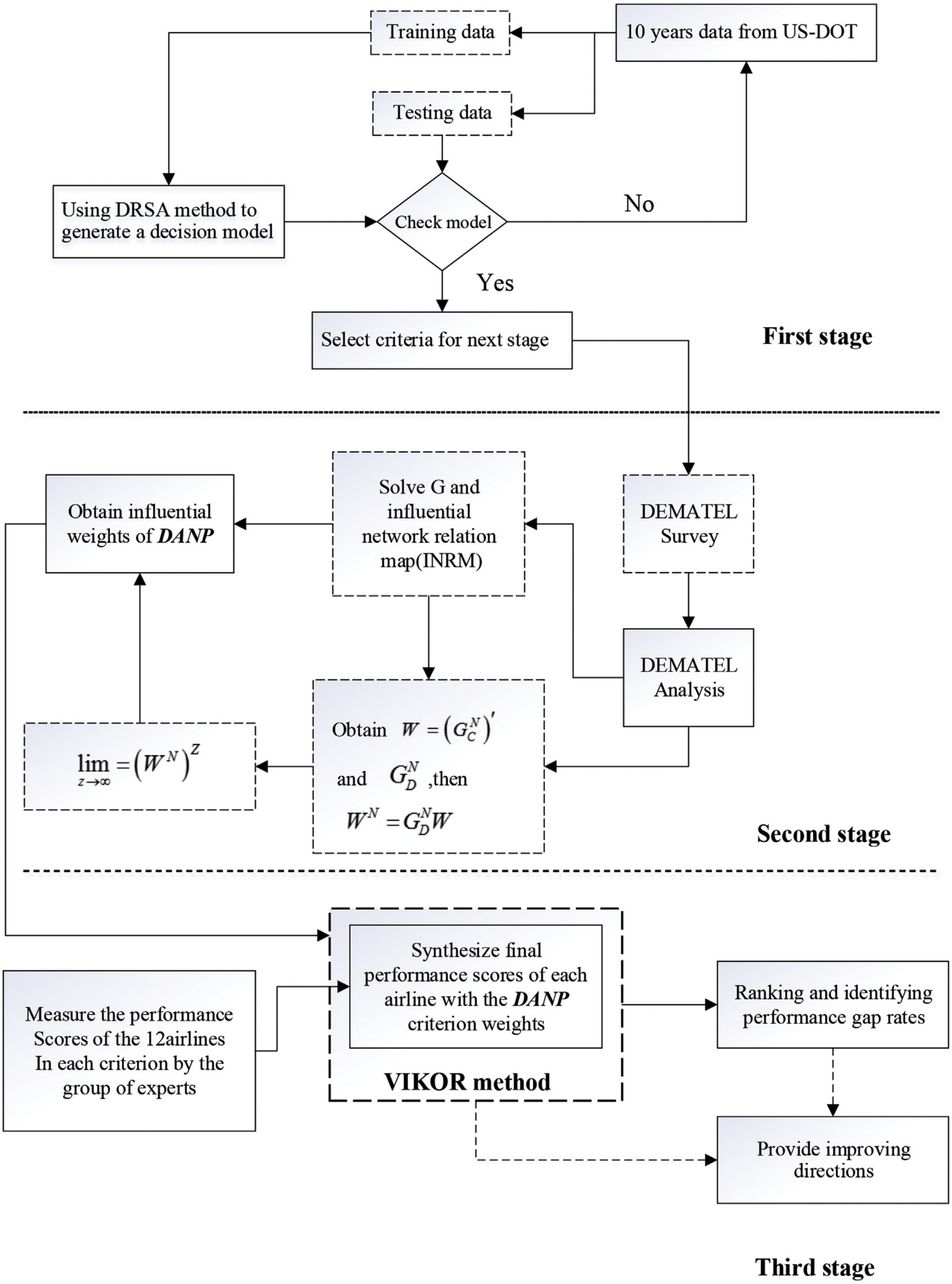

Fig. 1. The flow chart of the proposed model.

representation, by which the respondent organizes its action in the world. The purpose is to analyze the component structure of each factor, and the direction and intensity of direct and indirect relationships that flow between the components (Tzeng et al., 2007; Liou et al., 2016). The obtained influential network relationship map (INRM) can provide managers with directions for improvement. The method's 4 steps are summarized below:

Step 1: Calculation of the initial direct influence matrix ***A***.

For the calculation of matrix $\boldsymbol{A}$ (direct influence matrix) a group of experts are asked to identify the degree of influence between the factors or elements (criteria). Based on these scores the calculation of an average matrix is possible. The scores provided indicate the degree of influence factor i has over j factors, as indicated by a_{ij}. An integer scale is applied to rank the influence between the elements ranging from 0 to 4, where 0 = No influence and 4 = Very high influence. It is possible to derive an average $\boldsymbol{A}$ matrix from any group of direct matrices that proceed from the responses of the group of experts, where each element of the average matrix represents the mean of the responses for the same element provided by each expert.

Step 2: Calculation of the normalized $\boldsymbol{D}$ matrix.

Matrix $\boldsymbol{D}$ is calculated from the normalized influence matrix $\boldsymbol{D}$ which is obtained by $D = [d_{ij}]_{n\times n}$. The direct influence matrix $\boldsymbol{A}$ is normalized were $0 \le d_{ij} \le 1$, known as the "fuzzy cognitive matrix", in which all the principal diagonal elements are equal to zero. With matrix $\boldsymbol{D}$, it is possible to discover the initial effect that each element exerts and receives from another. As mentioned, the goal of DEMATEL is to map the interrelationship between all the elements of a system with the strength of the influence (degree of influence) represented by a number.

During the calculation of matrix $\boldsymbol{D}$, the full direct/indirect influence matrix must continuously decrease because of the indirect effects of problems with the powers of matrix $\boldsymbol{D}$, e.g., $\boldsymbol{D}^2, \boldsymbol{D}^3, \ldots, \boldsymbol{D}^\infty$ so that it will guarantee convergent solutions to the matrix inversion. With the above analysis it is possible to illustrate an infinite series of direct and indirect effects.

The matrix $\boldsymbol{D}$ can be calculated as follows:

$$\mathbf{D} = s \cdot \mathbf{A}, \quad s > 0, \tag{10}$$

where

$$s = \min\left[\frac{1}{\max_{1\le i\le n}\sum_{j=1}^{n}|a_{ij}|}, \frac{1}{\max_{1\le i\le n}\sum_{i=1}^{n}|a_{ij}|}\right]; \tag{11}$$

and

$$\lim_{m\to\infty} \mathbf{D}^m = [0]_{n\times n}, \quad \mathbf{D} = [d_{ij}]_{n\times n}, \quad 0 \le d_{ij} < 1.$$

Step 3: Calculation of the total-influence matrix $\mathbf{G}$.

The total-influence matrix $\mathbf{G}$ can be obtained by using Eq. (12)

$$\boldsymbol{G} = \boldsymbol{D} + \boldsymbol{D}^2 + \boldsymbol{D}^3 + \ldots + \boldsymbol{D}^{\boldsymbol{m}} = \boldsymbol{D}(\boldsymbol{I} - \boldsymbol{D})^{-1} \quad \text{when } m \ -> \infty. \tag{12}$$

Through Eqs. (13) and (14), it will be possible to define the sum of the rows and the sum of the columns separately which can be denoted as vector $\boldsymbol{r}$ and $\boldsymbol{c}$ within the total-influence matrix $\mathbf{G}$.

$$\mathbf{G} = \left[g_{ij}\right] \quad i,j = 1,2,\ldots,n;$$
$$\mathbf{r} = [r_i]_{n\times 1} = \left(\sum_{j=1}^{n} g_{ij}\right)_{n\times 1}; \tag{13}$$

$$\mathbf{c} = [c_i]'_{1\times n} = \left(\sum_{i=1}^{n} g_{ij}\right)'_{1\times n}, \tag{14}$$

where superscript ' denotes transport.

Suppose r_i denotes the row sum of the ith row in matrix $\boldsymbol{G}$, then r_i shows the sum of the direct and indirect effects of factor i on the other factors/criteria. If c_i denotes the column sum of the j th column of matrix $\boldsymbol{G}$, then c_i shows the sum of the direct and indirect effects that factor i has received from the other factors. Furthermore, when $i = j$ (i.e., the sum of the row and column aggregates) $(r_i + c_i)$ provides an index of the strength of influences given and received, that is, $(r_i + c_i)$, shows the degree of importance that factor i plays in the problem. If $(r_i - c_i)$ is positive, then factor i is affecting other factors and if $(r_i - c_i)$ is negative, then factor i is being influenced by other factors (Tzeng et al., 2007).

Step 4: Derivation of the influence network relationship map (INRM)

Based on matrix $\boldsymbol{G}$, each element g_{ij} of matrix $\boldsymbol{G}$, provides information about how element i affects or has influence over element j. By identifying and choosing the elements in matrix $\boldsymbol{G}$ with the highest influence level value compared to a threshold value, it is possible to finally construct the INRM. The threshold value can be decided through expert opinions obtained during brainstorming as well as by calculating an average for matrix $\boldsymbol{G}$. As long as the threshold value and the relative INRM have been decided, the final results of the DEMATEL process can be shown in an INRM.

3.3. The DEMATEL-based analytic network process

In this study, the DEMATEL-based ANP, which was developed by Lee et al. (2009), combining the original DEMATEL method and basic concepts of ANP (DANP), is applied to calculate the influential weights of the criteria. The DANP method can be summarized in 3 steps:

Step 1: Model construction and problem structuring

Using the INRM developed from the DEMATEL method, we can construct the interrelationships for the evaluation system. Based on the derived structure, the formation of a supermatrix can be decided.

Step 2: Integration of the DEMATEL and ANP to develop an unweighted supermatrix

The ANP method uses a "supermatrix". Pairwise comparisons are obtained by asking a group of experts questions like "How much importance (priority) does one criterion have compared to another criterion, with respect to our interests or preferences?" Through this process it is possible to identify the difference in importance between criteria. In this study, we adopt the results of DEMATEL, which indicate the degrees of influence between criteria, to transform the influence degrees into priority vectors between criteria. Eq. (15) shows the standard form of the DANP supermatrix developed based on the DEMATEL technique, using the previously mentioned matrix $\boldsymbol{G}$, normalized to $\boldsymbol{G}_{\boldsymbol{C}}^{\boldsymbol{N}}$ as in Eq. (15).

$$G_C^N = \begin{array}{cc} & \\ & \\ D_1 & \begin{matrix} c_{11} \\ c_{12} \\ \vdots \\ c_{1m_1} \end{matrix} \\ \vdots & \vdots \\ D_i & \begin{matrix} c_{i1} \\ c_{i2} \\ \vdots \\ c_{im_i} \end{matrix} \\ \vdots & \vdots \\ D_n & \begin{matrix} c_{n1} \\ c_{n2} \\ \vdots \\ c_{nm_n} \end{matrix} \end{array} \begin{array}{c} \begin{matrix} \quad D_1 & & D_j & & D_n \\ c_{11} \cdots c_{1m_1} & \cdots & c_{j1} \cdots c_{jm_j} & \cdots & c_{n1} \cdots c_{nm_n} \end{matrix} \\ \begin{bmatrix} G_c^{N11} & \cdots & G_c^{N1j} & \cdots & G_c^{N1n} \\ \vdots & & \vdots & & \vdots \\ G_c^{Ni1} & \cdots & G_c^{Nij} & \cdots & G_c^{Nin} \\ \vdots & & \vdots & & \vdots \\ G_c^{Nn1} & \cdots & G_c^{Nnj} & \cdots & G_c^{Nnn} \end{bmatrix} \end{array} \tag{15}$$

After the normalization of the total-influence matrix $\boldsymbol{G}$, the un-weighted supermatrix can be obtained by transposing $\boldsymbol{G_C^N}$, by setting $\boldsymbol{W} = (\boldsymbol{G_C^N})'$. In addition, to adjust the weights among dimensions, the dimensional matrix $\boldsymbol{G_D}$ is normalized to become $\boldsymbol{G_D^N}$ as follows:

$$\mathbf{G}_{\mathrm{D}} = \begin{bmatrix} g_{\mathrm{D}}^{11} & \cdots & g_{\mathrm{D}}^{1n} \\ \vdots & \ddots & \vdots \\ g_{\mathrm{D}}^{n1} & \cdots & g_{\mathrm{D}}^{nn} \end{bmatrix}; \tag{16}$$

$$\mathbf{G}_{\mathrm{D}}^{\mathrm{N}} = \begin{bmatrix} g_{\mathrm{D}}^{11}/d_1 & \cdots & g_{\mathrm{D}}^{1n}/d_1 \\ \vdots & \ddots & \vdots \\ g_{\mathrm{D}}^{n1}/d_n & \cdots & g_{\mathrm{D}}^{nn}/d_n \end{bmatrix} = \begin{bmatrix} g_{\mathrm{D}}^{\mathrm{N}11} & \cdots & g_{\mathrm{D}}^{\mathrm{N}1n} \\ \vdots & \ddots & \vdots \\ g_{\mathrm{D}}^{\mathrm{N}n1} & \cdots & g_{\mathrm{D}}^{\mathrm{N}nn} \end{bmatrix}. \tag{17}$$

The adjusted supermatrix can be obtained by multiplying $\boldsymbol{G_D^N}$ by the un-weighted supermatrix $\boldsymbol{W}$; and the limiting supermatrix can be derived by multiplying itself by itself multiple times until the weights become stable and converge as a weighted supermatrix $\boldsymbol{W^N} = \boldsymbol{G_D^N W}$. For a more detailed explanation of the calculation procedure please see Liou et al. (2016).

Step 3: Calculation of the influential weights of the criteria

As a final step to calculate the influential weights of each criterion, the weighted supermatrix can be raised to limiting powers, as in Eq. (18). In general, the process of raising power z can be stopped when the limiting supermatrix becomes stable. The final product of the DANP will give us the platform to make better decisions based on the weights. These are then used with the VIKOR method for weighted gap analysis and finally to make decision proposals.

$$\lim_{z \to \infty} = \left(\mathbf{W}^N\right)^z. \tag{18}$$

3.4. Using the modified VIKOR method to find the gaps to the aspiration level

The modified VIKOR method applied in the present study differs from the traditional method derived by Opricovic (1998) and Opricovic and Tzeng (2004, 2007). The traditional VIKOR method is used to produce a multiple-criteria ranking index, which is based on a measure of proximity to the ideal solution, a concept of relative good. The modified VIKOR method replaces the relative good with aspiration levels reflecting the real world situation.

The VIKOR method (Opricovic, 1998; Opricovic and Tzeng, 2004, 2007; Liou et al., 2011; Saketa et al., 2015; Hsu et al., 2017) is explained as follows:

Step 1: An aggregation function is carried out to form a compromise ranking

According to Yu (1973), it is necessary to begin with an L_p *metric* which is used as an aggregation function to form the compromise ranking. The L_p *metric* can be represented by

$$L_k^P = \left\{ \sum_{j=1}^{n} \left[w_j \left(\left| f_j^* - f_{kj} \right| \right) / \left(\left| f_j^* - f_j^- \right| \right) \right]^P \right\}^{1/P}, \quad 1 \le p \le \infty; \ k = 1, \ldots, m \tag{19}$$

Step 2: The indexes S_k and R_k

In this step, it is necessary to calculate the indexes S_k formulated as in Eq. (20) and R_k formulated in Eq. (21), while $p = 1$ and $p = \infty$, respectively.

$$S_k = L_k^{P=1} = \sum_{j=1}^{n} \left[w_j \left(\left| f_j^* - f_{kj} \right| \right) / \left(\left| f_j^* - f_j^- \right| \right) \right]; \tag{20}$$

$$R_k = L_k^{P=\infty} = \max_j \left\{ w_j \left(\left| f_j^* - f_{kj} \right| \right) / \left(\left| f_j^* - f_j^- \right| \right) | j = 1, 2, \ldots, n \right\}. \tag{21}$$

In Eqs. 20 and 21, the best value is denoted by f_j^*, defined as the aspiration level on the j th criterion; f_j^- denotes the tolerable value on the j th criterion. The results of indexes S_k and R_k form the compromise ranking index Q_k based on the weighted group utility (i.e., weight $= v$) and individual regret (i.e., weight $= 1 - v$) as follows:

$$Q_k = v \times \frac{(S_k - S^*)}{(S^- - S^*)} + (1 - v) \times \frac{(R_k - R^*)}{(R^- - R^*)}. \tag{22}$$

Traditionally, this approach uses $S^* = \min_k\{S_k | k = 1, 2, \ldots, m\}$ and $S^- = \max_k\{S_k | k = 1, 2, \ldots, m\}$; as well as $Q^* = \min_k\{Q_k | k = 1, 2, \ldots, m\}$ and $Q^- = \max_k\{Q_k | k = 1, 2, \ldots, m\}$ in Eq. (22). Setting f_j^* as the aspiration level and f_j^- as the tolerable value, then we can get $S^* = Q^* = 0$ and $S^- = Q^- = 1$. Therefore, Eq. (22) can be re-written as Eq. (23).

Table 2
Attributes used in the DRSA method.

Attribute (Criterion)	Domain values	Value set	Dimension
Decision attribute			
Operative profit or loss/net income (d_1)	$d_1 \leq 0$; $0 < d_1 \leq 1$; $1 < d_1$	{0, 1, 2}	Finance
On time performance (d_2)	$d_2 \leq 80\%$; $80\% < d_2$	{1, 2}	Operation
Condition attribute			
Net income	In thousand dollars	Continue	Finance
Operative profit/loss	In thousand dollars	Continue	Finance
Operative revenue	In thousand dollars	Continue	Finance
Baggage fees	In thousand dollars	Continue	Finance
Reservation charges fees	In thousand dollars	Continue	Finance
Operative expenses	In thousand dollars	Continue	Finance
Stock's price	Dollars in NYSE/NASDA	Continue	Finance
Fuel cost and consumption	In thousand dollars	Continue	Finance
Labor	Number of people	Continue	Finance
Available Seat-miles	Number of seats and the distance flown in thousands	Continue	Operation
Load factor	Passenger-miles as a proportion of available seat-miles in percent	Continue	Operation
Flights	Units	Continue	Operation
Freight	In Thousands of Dollars $000	Continue	Operation
Mishandled Baggage	Per 1000 passengers	Continue	Operation
Passengers	Number of people	Continue	Operation
Air Carrier delays as domino effect	Percentage (%)	Continue	Operation
Weather delays	Percentage (%)	Continue	Operation
Security delays	Percentage (%)	Continue	Operation
Aircraft arriving late	Percentage (%)	Continue	Operation
Canceled flights	Percentage (%)	Continue	Operation
National aviation system delays	Percentage (%)	Continue	Operation

$$Q_k = \nu \times S_k + (1 - \nu) \times R_k. \tag{23}$$

4. Empirical example from a real-world case of financial and operational performance

To illustrate the effectiveness and usefulness of the proposed model, it is applied to a real-world case.

4.1. Background and problem description

There has been considerable fluctuation in the finances and operations of airlines in the last ten years because of fuel price fluctuations, global financial crises, and a reduction in the number of passengers caused by terrorism. Improper financial and operational management decisions might also affect internal costs, resulting in high-risk situations. Airline managers need a useful tool to help them identify, diagnose, and rank the factors affecting decisions and make plans for improvement of financial and operational performance. The MCDM data mining technique provides a useful for this purpose because it can combine all the factors of concern to generate acceptable solutions. The solution method can be divided into four stages: (1) In the first state, the DRSA method is applied to explore historical data and to identify essential factors (criteria) related to airlines' operation and financial performance; (2) the DEMATEL method is then applied to determine the interrelationship among the essential criteria by applying the responses of a survey of a group of experts asked to evaluate the influences among the criteria; (3) the influential weights of the essential criteria are derived by the DANP method; and (4) a modified VIKOR method is applied to help managers identify the priorities of weighted gaps for improvement.

4.2. Extracting essential decision variables using the DRSA method

The proposed model developed in this study was tested using over 10 years (2005–2014) of real data provided by the Office of the Assistant Secretary for Research and Technology of the United States Department of Transportation (2016). The raw data were obtained from the monthly released reports for the top 12 airlines in the United States, which are currently transporting passengers and cargo. The data set included two types of variables—financial and operational. Because the inclusion of all variables in the analysis is not practical, we first applied DRSA to extract the most essential variables of both types. Among financial variables, operating profit or loss/net income was set as the decision variable, whereas the remaining were considered condition variables; three levels of the decision value were considered: good (>1), medium (0–1), and poor (<0). Among operational variables, on-time performance percentage was set as the decision variable with two levels: good (≥80%) and poor (<80%). The attributes and their domain values are presented in Table 2.

Through DRSA analysis, we derived a set of rules having the most relevant factors/criteria for the airlines' financial and operational performance. Table 3 lists the financial and operational efficiency quality approximations. The results showed a very good quality of approximation with minimum accuracy (0.833) at union of at most 0. The derived set of rules having at least medium or good support are presented in Table 4. These rules present higher correction with good airline performance. From Table 4, 11 criteria for the rules with high support rates were extracted for the next stage of analysis. The DRSA method enabled the identification of the critical factors (criteria) to be considered by ascertaining the presence or frequency of these in the decision rules and excluding

Table 3
Financial and operational efficiency quality approximation.

	Financial efficiency Quality of approximation: 0.975		Operational efficiency Quality of approximation: 1.00	
Union names	Accuracy	Cardinality	Accuracy	Cardinality
At most 0	0.833	17	1.000	5
At least 1	0.971	102	1.000	115
At most 1	0.889	26	1.000	83
At least 2	0.968	93	1.000	37

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Table 4
Minimum cover rules for a decision, which is at least medium or good.

No.	Conditions	Decision	Support
Financial dimension			
1	(Labor ≤ 3067.0)	$d_1 \geq 2$	8
2	(Baggage fees ≥ 862909.0)	$d_1 \geq 2$	4
3	(Operative revenue ≥ 3.8287134E7)	$d_1 \geq 2$	3
4	(Net income ≥ 87468.0) & (Labor ≤ 47286.0)	$d_1 \geq 2$	37
5	(Operative profit or loss ≥ 14248.0) & (Stock's price ≥ 35.65)	$d_1 \geq 2$	17
6	(Baggage fees ≥ 64078.0) & (Fuel cost and consumption ≤ 1663606.0)	$d_1 \geq 2$	17
7	(Baggage fees ≥ 14316.0) & (Stock's price ≥ 38.74)	$d_1 \geq 2$	12
8	(Net income ≤ 10984.0) & (Labor ≤ 3635.0)	$d_1 \geq 2$	8
9	(Net income ≥ 13525.0) & (Operative profit or loss ≥ 43780.0) & (Labor ≤ 12638.0)	$d_1 \geq 2$	45
10	(Baggage fees ≥ 13555.0) & (Labor ≤ 9269.0)	$d_1 \geq 2$	23
11	(Operative revenue ≥ 1131705.0) & (Labor ≤ 4034.0)	$d_1 \geq 2$	8
12	(Baggage fees ≥ 475184.0) & (Fuel cost and consumption ≤ 4857093.0)	$d_1 \geq 2$	2
13	(Operative revenue ≥ 2.3957565E7) & (Fuel cost and consumption ≤ 7153077.0)	$d_1 \geq 2$	2
Operational dimension			
1	(Freight ≥ 922630.0)	$d_2 \geq 2$	1
2	(Freight ≥ 6041.0) & (Weather delays ≤ 0.21)	$d_2 \geq 2$	11
3	(Freight ≥ 6857.0) & (Diverted delays ≤ 0.09)	$d_2 \geq 2$	11
4	(Cancelled flights ≤ 0.33) & (National aviation system delays ≤ 6.14)	$d_2 \geq 2$	14
5	(Security delays ≤ 0.08) & (National aviation system delays ≤ 2.78)	$d_2 \geq 2$	18
6	(Aircraft arriving late ≤ 4.61) & (National aviation system delays ≤ 6.56)	$d_2 \geq 2$	20
7	(Air Carrier delays as domino effect ≤ 4.31) & (Aircraft arriving late ≤ 6.46)	$d_2 \geq 2$	15
8	(Cancelled flights ≤ 0.33) & (National aviation system delays ≤ 6.14)	$d_2 \geq 2$	9
9	(Air Carrier delays as domino effect ≤ 4.96) & (National aviation system delays ≤ 4.92)	$d_2 \geq 2$	21

Table 5
Dimensions and criteria for airline performance improvement.

Goal	Dimensions	Criteria
Establish performance improvement planning goals per airline	Internal financial factors (D_1)	Net income (C_{11})
		Operative profit (C_{12})
		Operative revenue (C_{13})
		Operative expenses (C_{14})
	External financial factors (D_2)	Stock's price (C_{21})
		Fuel cost and consumption (C_{22})
	Internal operational factors (D_3)	Available Seat-miles (C_{31})
		Freight (C_{32})
		Air Carrier delays as domino effect (C_{33})
	External operational factors (D_4)	Aircraft arriving late (C_{41})
		Diverted delays (C_{42})

non-relevant criteria. The 11 extracted criteria were further divided by internal and external dimensions as shown in Table 5.

4.3. Using the DEMATEL method to measure the relationships among criteria

After defining the criteria, we invited aviation experts to survey and explore the interrelationship among the criteria and the direction of influence. We surveyed 20 experts from eight airlines, namely United Airlines, American Airlines, US Airways, Delta Air Lines, Spirt Airlines, Emirates, Copa Airlines, and Avianca. The experts were or had worked as airline station managers, station supervisors, operations supervisors, or hub or headquarter administrative personnel. The experts were asked to determine the level of influence among the criteria based on which we established matrix $\boldsymbol{A}$ by calculating the average number produced from the DEMATEL survey. The average initial direct-relation 11 × 11 matrix $\boldsymbol{A}$ was obtained by pairwise comparisons in terms of the influences and directions of influence among criteria (Table 6).

From Table 6, the normalized direct-relation $\boldsymbol{D}$ was calculated by

Table 6
Initial influence matrix $\boldsymbol{A}$.

$\boldsymbol{A}$	C_{11}	C_{12}	C_{13}	C_{14}	C_{21}	C_{22}	C_{31}	C_{32}	C_{33}	C_{41}	C_{42}
C_{11}	0.00	0.00	0.00	0.00	3.25	0.00	2.75	2.00	0.00	0.00	0.00
C_{12}	3.25	0.00	0.00	0.00	2.50	0.00	0.00	0.00	0.00	0.00	0.00
C_{13}	3.75	3.00	0.00	2.75	2.88	2.00	2.38	0.00	0.00	0.00	0.00
C_{14}	3.13	3.00	0.00	0.00	2.25	0.00	2.63	0.00	0.00	0.00	0.00
C_{21}	2.50	2.00	0.00	2.13	0.00	1.88	0.00	0.00	0.00	0.00	0.00
C_{22}	3.13	3.38	0.00	3.50	2.38	0.00	2.25	3.00	2.25	2.25	1.75
C_{31}	2.75	2.88	2.38	2.50	2.63	2.13	0.00	2.25	2.25	2.00	2.13
C_{32}	2.88	2.63	2.75	2.88	2.13	2.25	0.00	0.00	2.00	2.13	2.13
C_{33}	3.25	3.00	2.75	2.50	2.50	2.25	2.13	2.63	0.00	3.00	1.75
C_{41}	2.63	2.88	2.50	3.13	2.13	2.13	1.88	2.25	2.63	0.00	0.00
C_{42}	2.38	2.75	2.50	3.00	2.13	2.50	2.38	2.50	3.13	2.63	0.00

Table 7
Total influence matrix $\boldsymbol{G}$.

$\boldsymbol{G}$	C_{11}	C_{12}	C_{13}	C_{14}	C_{21}	C_{22}	C_{31}	C_{32}	C_{33}	C_{41}	C_{42}
C_{11}	0.05	0.04	0.02	0.04	0.15	0.03	0.11	0.09	0.02	0.02	0.02
C_{12}	0.13	0.01	0.00	0.01	0.10	0.01	0.01	0.01	0.00	0.00	0.00
C_{13}	0.21	0.16	0.02	0.14	0.17	0.10	0.13	0.04	0.02	0.02	0.02
C_{14}	0.15	0.13	0.01	0.03	0.12	0.02	0.11	0.02	0.01	0.01	0.01
C_{21}	0.12	0.10	0.01	0.09	0.04	0.07	0.03	0.02	0.01	0.01	0.01
C_{22}	0.25	0.22	0.06	0.21	0.20	0.07	0.15	0.16	0.12	0.12	0.09
C_{31}	0.24	0.21	0.13	0.18	0.21	0.14	0.08	0.14	0.12	0.12	0.10
C_{32}	0.23	0.19	0.13	0.18	0.19	0.13	0.08	0.06	0.11	0.11	0.10
C_{33}	0.26	0.22	0.15	0.19	0.22	0.15	0.16	0.16	0.06	0.15	0.09
C_{41}	0.22	0.20	0.13	0.19	0.19	0.13	0.13	0.13	0.12	0.04	0.03
C_{42}	0.24	0.23	0.14	0.21	0.21	0.16	0.17	0.16	0.16	0.14	0.04

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Table 8
Sum of influences given and received on criteria.

G	C_{11}	C_{12}	C_{13}	C_{14}	C_{21}	C_{22}	C_{31}	C_{32}	C_{33}	C_{41}	C_{42}
r	0.58	0.30	1.03	0.65	0.51	1.66	1.68	1.50	1.80	1.52	1.86
c	2.10	1.73	0.80	1.47	1.81	0.99	1.16	0.99	0.77	0.75	0.52
$r+c$	2.68	2.03	1.82	2.12	2.32	2.65	2.84	2.50	2.57	2.27	2.38
r-c	−1.52	−1.42	0.23	−0.82	−1.30	0.67	0.52	0.51	1.03	0.76	1.34

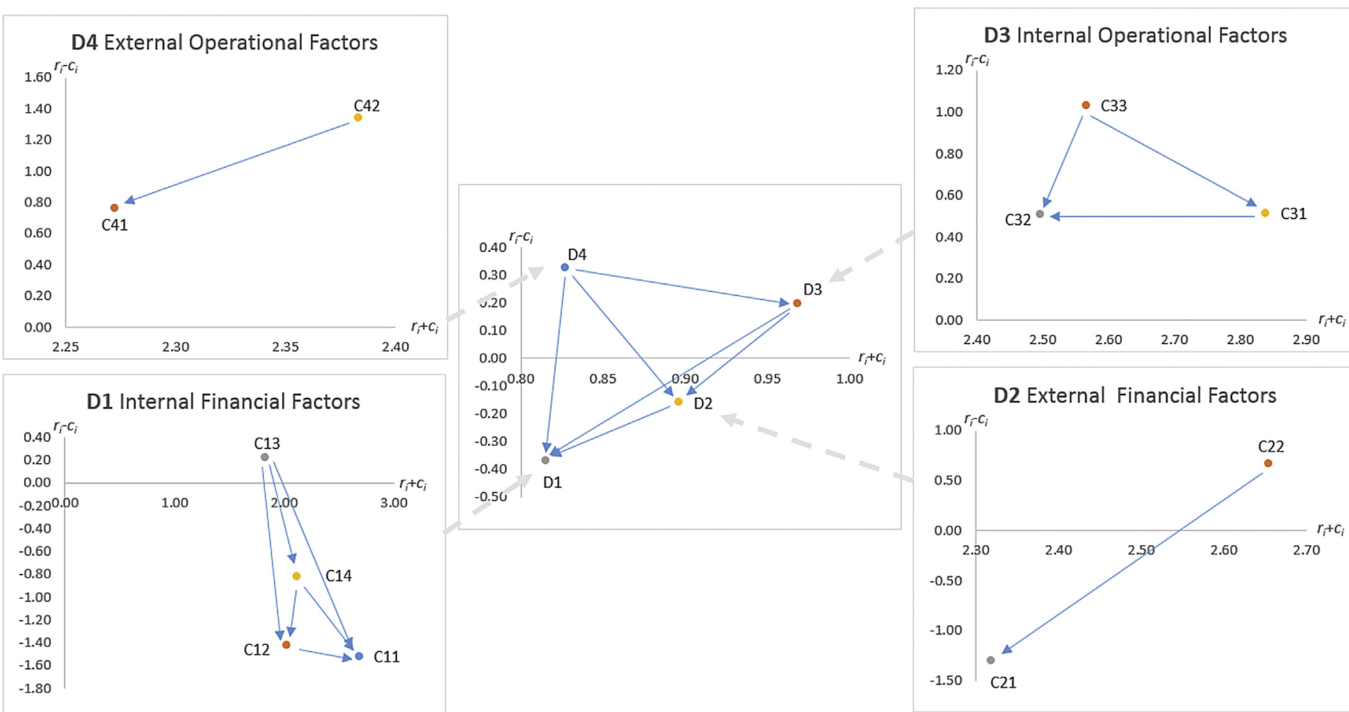

Fig. 2. INRM of the evaluation system.

applying Eqs. (10) and (11). We then derived the total influence matrix $\boldsymbol{G}$ by using Eq. (12) (Table 7). The sum of the influence given and received by each dimension was calculated with Eqs. (13) and (14) (Table 8). The influence network relation map (INRM) plotted using the total influence matrix $\boldsymbol{G}$ and Table 8 is illustrated in Fig. 2. From the INRM, the direction of influence between dimensions and criteria can be visualized. The INRM indicates that the external operational dimension (D_4) is marked by an arrow pointing toward the internal operational dimension (D_3). This shows how external criteria (uncontrollable factors in managerial terms) can directly affect the internal criteria (controllable factors). Furthermore, the arrow pointing from the external financial dimension (D_2) toward the internal financial dimension (D_1) indicates that all actions and dimensions directly affect the costs, expenses, and profitability. The network relationship within dimension (D_1) indicates that all criteria directly or indirectly affect the net income (C_{11}), which is located in the extreme lower part of the graph, with all arrows pointing toward it. This result indicates that all actions or influential factors in an airline consequently involve some type of cost or expense. In addition, external factors affect internal factors, indicating that minimizing the negative impact of any external operational factors (D_4) can improve the internal operational factors (D_3). The INRM results also indicates that fuel cost (C_{22}) is the causative factor within subsystem D_2 and that the influence of D_2 on D_1 implies that fuel cost is the key factor affecting the airlines' financial performance.

4.4. Using the DANP method to obtain influential weights of criteria

After the DEMATEL analysis, the relationship structure between all criteria was derived and the structure of the supermatrix was confirmed. The DANP method was used to obtain the influential weights of the criteria. Based on the DEMATEL results, we adjusted the weight vectors to create dimension matrixes $\boldsymbol{G_D}$ and $\boldsymbol{G_D^N}$ by using Eqs. (16) and (17) followed by a weighted supermatrix (Table 9). Eq. (18) was applied to calculate the limiting power of the weighted supermatrix as indicated in Table 10; the final influential weights produced for each criterion and dimension are shown in

Table 9
Weighted supermatrix.

	C_{11}	C_{12}	C_{13}	C_{14}	C_{21}	C_{22}	C_{31}	C_{32}	C_{33}	C_{41}	C_{42}
C_{11}	0.33	0.82	0.39	0.47	0.39	0.33	0.31	0.31	0.32	0.30	0.30
C_{12}	0.28	0.08	0.31	0.40	0.30	0.31	0.28	0.26	0.27	0.27	0.27
C_{13}	0.14	0.02	0.04	0.04	0.02	0.08	0.17	0.18	0.18	0.17	0.17
C_{14}	0.25	0.08	0.26	0.09	0.29	0.28	0.24	0.25	0.23	0.26	0.26
C_{21}	0.83	0.92	0.64	0.85	0.36	0.75	0.61	0.59	0.60	0.60	0.57
C_{22}	0.17	0.08	0.36	0.15	0.64	0.25	0.39	0.41	0.40	0.40	0.43
C_{31}	0.51	0.50	0.67	0.74	0.47	0.34	0.24	0.32	0.42	0.34	0.35
C_{32}	0.40	0.39	0.21	0.16	0.34	0.37	0.40	0.24	0.42	0.34	0.33
C_{33}	0.09	0.11	0.13	0.09	0.18	0.28	0.36	0.43	0.15	0.32	0.33
C_{41}	0.53	0.54	0.55	0.53	0.56	0.57	0.53	0.54	0.61	0.56	0.77
C_{42}	0.47	0.46	0.45	0.47	0.44	0.43	0.47	0.46	0.39	0.44	0.23

Table 10
Limiting supermatrix.

	C_{11}	C_{12}	C_{13}	C_{14}	C_{21}	C_{22}	C_{31}	C_{32}	C_{33}	C_{41}	C_{42}
C_{11}	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13
C_{12}	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
C_{13}	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
C_{14}	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08
C_{21}	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21
C_{22}	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10
C_{31}	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10
C_{32}	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07
C_{33}	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
C_{41}	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07
C_{42}	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06

Table 11. The calculated influential weights reflect the importance of each factor (criterion) involved in the decision-making process. According to Table 11, the top priority criteria in global weights is the stock price (global rank priority #1) and net income (global rank priority #2), indicating how carefully managers must manage overall operational performance to achieve the best financial performance as a primary goal.

4.5. Using the VIKOR method to explore the gaps to the aspiration levels

After obtaining the criterion weights (Table 11), we asked the same group of domain experts to analyze the 10 years of historical data, considering each dimension of financial and operational performance. The results of the evaluation of all the criteria and determination of the evaluation score of each alternative and historical performance are summarized in Table 12. The experts were asked to evaluate 12 US airlines (alternatives), considering different geographical location hubs, fleet sizes, number of employees, and market segments. The experts evaluated historical data and were asked to rate performance as "excellent", "very good", "good", "considerable", "poor", or "bad" based on the data. They also ranked performance on a scale of 1–10, where 1 indicated bad performance and 10 excellent performance. After obtaining the average score from the experts' responses (Table 12) and applying Eqs. (20)–(23), the final ranking of the airlines with the best financial and operational performance was determined on the basis of the DANP weights and VIKOR method results, as presented in Table 13.

5. Results and discussion

Some crucial management implications can be derived from our analysis. As can be seen in Table 11, the dimension of internal financial factor (D_1) had the highest weight (34%), followed by external financial factors (D_2; 32%), indicating that managers should consider financial criteria to be more critical than other operational criteria. The INRM results (Fig. 2) indicated a logical path for strategic planning to reach the main goals for improvement. We observe that operational criteria (in D_3 and D_4) are the cause and financial criteria (in D_1 and D_2) are the effect. In other words, the order of improvement should begin with operational factors which would influence the financial performance. Our case study results show that controllable factors should have the highest priority among managerial tasks because of the capacity to rapidly correct controllable actions. Managers must take action in relation to controllable factors in order to reach optimization goals and minimize the negative impact of the uncontrollable factors.

Among the criteria, stock price (C_{21}) had the top priority (21%) in the global ranking weights (see Table 11) and was located at the center of the INRM (see Fig. 2), because it is affected by operational factors and can influence other internal financial criteria. The

Table 11
Influential weights on criteria and dimensions.

Dimension	Local weight	Ranking	Criteria	Local weight	Ranking	Global weight	Ranking
D_1	0.34	1	C_{11}	0.39	1	0.13	2
			C_{12}	0.28	2	0.09	5
			C_{13}	0.10	4	0.03	11
			C_{14}	0.23	3	0.08	6
D_2	0.32	2	C_{21}	0.67	1	0.21	1
			C_{22}	0.33	2	0.10	3
D_3	0.22	3	C_{31}	0.44	1	0.10	4
			C_{32}	0.34	2	0.07	7
			C_{33}	0.22	3	0.05	10
D_4	0.13	4	C_{41}	0.56	1	0.07	8
			C_{42}	0.44	2	0.06	9

Table 12
Original evaluation score of alternatives.

Dimension/ criteria		A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}
D_1	C_{11}	6.15	5.54	5.46	8.31	6.46	7.08	6.38	7.69	5.38	5.77	5.54	6.00
	C_{12}	7.31	6.92	6.46	7.31	6.23	6.92	6.62	7.54	6.08	5.92	4.85	3.92
	C_{13}	8.54	7.69	6.69	8.38	6.77	6.92	7.85	7.31	6.54	6.69	5.69	5.69
	C_{14}	6.62	6.38	6.62	5.62	6.54	6.85	6.62	6.08	6.54	6.15	6.23	6.31
D_2	C_{21}	8.00	7.15	7.77	6.69	5.62	7.31	6.23	7.69	5.31	4.15	6.54	6.62
	C_{22}	6.62	6.54	6.46	6.23	5.69	6.46	5.92	6.00	6.31	5.77	4.77	5.08
D_3	C_{31}	7.77	8.23	6.69	7.69	6.38	6.31	7.08	6.62	7.23	6.54	6.15	6.46
	C_{32}	8.15	6.92	6.62	7.85	6.23	5.77	5.85	5.85	7.46	6.00	5.15	6.92
	C_{33}	7.15	6.00	5.85	5.85	5.77	7.00	6.46	6.08	6.54	6.46	6.38	6.00
D_4	C_{41}	8.38	6.92	6.08	4.69	6.00	7.31	7.00	5.23	4.69	5.54	4.92	4.38
	C_{42}	7.62	7.08	5.23	7.08	6.77	6.69	7.69	5.85	5.54	6.85	5.85	5.77

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Table 13
Overall synthesized priorities for alternatives.

Dimension/criterion	Local weight	Global weight	VIKOR											
			A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}
D_1	0.34	–	0.32	0.37	0.39	0.26	0.36	0.30	0.34	0.28	0.40	0.40	0.45	0.45
C_{11}	0.39	0.13	0.38	0.45	0.45	0.17	0.35	0.29	0.36	0.23	0.46	0.42	0.45	0.40
C_{12}	0.28	0.09	0.27	0.31	0.35	0.27	0.38	0.31	0.34	0.25	0.39	0.41	0.52	0.61
C_{13}	0.10	0.03	0.15	0.23	0.33	0.16	0.32	0.31	0.22	0.27	0.35	0.33	0.43	0.43
C_{14}	0.23	0.08	0.34	0.36	0.34	0.44	0.35	0.32	0.34	0.39	0.35	0.38	0.38	0.37
D_2	0.32	–	0.25	0.30	0.27	0.35	0.44	0.30	0.39	0.29	0.44	0.53	0.40	0.39
C_{21}	0.67	0.21	0.20	0.28	0.22	0.33	0.44	0.27	0.38	0.23	0.47	0.58	0.35	0.34
C_{22}	0.33	0.10	0.34	0.35	0.35	0.38	0.43	0.35	0.41	0.40	0.37	0.42	0.52	0.49
D_3	0.22	–	0.22	0.27	0.35	0.27	0.38	0.37	0.35	0.38	0.28	0.37	0.41	0.35
C_{31}	0.44	0.10	0.22	0.18	0.33	0.23	0.36	0.37	0.29	0.34	0.28	0.35	0.38	0.35
C_{32}	0.34	0.07	0.18	0.31	0.34	0.22	0.38	0.42	0.42	0.42	0.25	0.40	0.48	0.31
C_{33}	0.22	0.05	0.28	0.40	0.42	0.42	0.42	0.30	0.35	0.39	0.35	0.35	0.36	0.40
D_4	0.13	–	0.20	0.30	0.43	0.43	0.37	0.30	0.27	0.45	0.49	0.39	0.47	0.50
C_{41}	0.56	0.07	0.16	0.31	0.39	0.53	0.40	0.27	0.30	0.48	0.53	0.45	0.51	0.56
C_{42}	0.44	0.06	0.24	0.29	0.48	0.29	0.32	0.33	0.23	0.42	0.45	0.32	0.42	0.42
Total performance/gap			0.26	0.32	0.35	0.31	0.39	0.32	0.35	0.32	0.40	0.43	0.43	0.42
Ranking			1	4	7	2	8	3	6	5	9	12	11	10

higher priority of stock price (C_{21}) should be reflected in the managers' priority to maximize profit. Another reason for the higher priority is that some airlines allow its employees to buy or are awarded company stocks as a bonus. Moreover, in terms of the criteria within internal financial factors, our results showed that net income (C_{11}) has the second highest priority (13%), whereas operating revenue (C_{13}) has the lowest priority among the airline performance criteria. According to these results, operational factors have a direct effect on financial factors, with internal financial factors (D_1) deemed essential because all other criteria involved in the performance analysis directly or indirectly influence net income (C_{11}), indicating that any action or decision has direct effects in monetary terms. This result can also be observed by looking at the INRM (Fig. 2) (lower part of the dimension (D_1)). C_{11} is influenced by all other criteria with the largest ($r + c$) value. Notably, although diverted delays (C_{42}) has the lowest priority in the evaluation system, it has the highest net influence ($r - c$) value (Table 8). This indicates that external operational factors are the root cause, directly or indirectly influencing other criteria.

Furthermore, as per the INRM (Fig. 2), the external operational and financial dimensions can influence the internal financial criteria. However, the external operational and financial conditions are subject to uncertainty (e.g., weather or runway conditions, in the case of external operational factors, international incidents, regional economic and financial situations, politics, and stock market speculation, on the external financial side). Results indicate that internal operations should be adjusted on the basis of the external conditions in order to improve the company's internal financial performance. However, managers should first check to see if the internal operational factors are performing efficiently to minimize the adversities of the external conditions, and then consider other criteria.

Table 13 shows the overall synthesized gap for each alternative (airline). Delta Air Lines (A_1) is the best performing airline with the lowest gap of 0.26, followed by Southwest Airlines (A_4; 0.31), Alaska Airlines (A_6; 0.32), and United Airlines (A_2; 0.32). Table 13 presents the strengths and weaknesses of these companies in detail. Based on the strengths, weaknesses, and derived INRM, airline managers can develop a strategy to improve their performance. For example, Delta Airlines (A_1) had strong efficiency in operating revenue (C_{13}; gap rate, 0.15), aircraft arriving late (C_{41}; gap rate, 0.16), and freight management (C_{32}; gap rate, 0.18); in contrast, its weaknesses included net income (C_{11}), with a high gap rate of 0.38, followed by operating expenses (C_{14}; gap rate, 0.34), and fuel cost and consumption (C_{22}; gap rate, 0.34). According to the INRM (Fig. 2), the priority for improvement should be air carrier delays which has a domino effect (C_{33}), because this has the highest gap rate (0.28) among the operational factors.

The internal operational factors influence the internal financial factors. It is thus logical to start from these internal operational factors. From this viewpoint, an internal change can influence external financial factors, for example, stock prices. Moreover, improved internal efficiency can mitigate the impact of uncontrollable external negative factors, whether operational or financial. For example, bad weather, which is an uncontrollable external factor, can reduce the percentage of on-time performance but, if we have efficient internal operational and financial performance, the negative impact of this or any other external factor can gradually be mitigated. By managing, planning, and using more effective tools to improve schedule alterations caused by air carrier delays (the domino effect) (C_{33}), the different factors involved in handling the available seat-miles (C_{31}) and freight (C_{32}) may be improved. Improvement of these aforementioned factors can influence the amount of operating revenue (C_{13}) and improvement in terms of appropriately managing and minimizing operating expenses (C_{14}) can increase operating profit (C_{12}), ultimately reaching the goal of maximizing net income (C_{11}). Logically, internal controllable factors may also affect external financial factors. In the INRM (in Fig. 2), an upper position indicates an influence on internal financial operational factors. Internal improvement can aid in influencing external factors, as in case of stock price (C_{21}), possibly minimizing the negative effects of fuel price increases and fluctuations. Fuel cost and consumption (C_{22}) is also an uncontrollable factor, but its negative effects can be reduced if internal improvements reach a significant level. In the case of external operational factors, the diverted delays (C_{42}) criterion influences late aircraft arrival (C_{41}). Both of these are mapped in the top section of the INRM indicating that they influence all other factors. Internal limitations are influenced by physical factors, such as wind conditions and flight plans for established international routes. In both cases, any negative effect can impact all other dimensions; however, if improvement is made in the handling of controllable factors, this may mitigate the negative impact of external factors.

The results obtained using our hybrid model should help airline managers make better decisions. The proposed model is efficient and useful because it relies upon real databases as well as the consensus of judgement from a diverse group of highly experienced airline staff, in this case, from eight full-service airlines, including some of the top US airlines. In general, according to the results in Table 8 and the INRM, it can be seen that diverted delays (C_{42}) and air carrier delays have a domino effect (C_{33}) and are critical criteria within causative factors (larger $r-c$ value), whereas available seat-miles (C_{31}) and net income (C_{11}) are critical criteria in the category of effect factors (larger $r+c$ value). The results of gap analysis (Table 12) indicate that improvement in controllable operational criteria should improve financial performance. This practical and flexible tool can help airline managers make decisions and set priorities to focus on customer service and maintain control over operational costs in order to improve company competitiveness and profitability within the industry. The results demonstrate that the proposed model is suitable to make these decisions, saving time by predefining priority weights and, in combination with the VIKOR method, allowing flexibility. Airline managers can realize their weaknesses and strengths from historical data and understand the gaps to the aspiration levels. The most feasible changes and improvement alternatives can be managed with versatility according to external and internal operational conditions and available sources depending on the individual airline.

6. Conclusions

In this study, we proposed an integrated soft computing model to solve the airline financial and operational performance problem. Our hybrid model combined DRSA, DEMATEL, DANP, and VIKOR methods to rank and identify the financial and operational critical factors. The model also explored the interrelationship and influence among the critical factors, the priority weights between them, which was the best performing airline, and the gap rates for each airline performance, in order to identify strengths and weaknesses in performance and directions for improvement. The DRSA method was used to extract 11 essential criteria from the original database with 22 criteria. DEMATEL analysis was carried out to show that financial factors are directly influenced by external and internal operational and external financial factors. In other words, controllable factors, both internal operational and financial, comprise the starting point for improvement. The DANP method enabled the discovery that the internal financial factor (D_1) is the most critical with the highest weight within dimensions; stock price (C_{21}) has the top global weight priority, followed by net income (C_{11}) within the criteria. The INRM confirmed that all remaining criteria influenced stock price (C_{21}) and net income (C_{11}) and that diverted delays (C_{42}) and air carrier delays are most critical to the domino effect (C_{33}). The VIKOR method was used to ranking the best performing companies and the gaps to the aspiration levels for each airline. This provided each airline with a benchmark reference and an indication of directions for improvement based on the gap priority within the operational criteria. Thus, our proposed model is a useful and effective tool for airlines to understand their strengths, weaknesses, and priorities for improvement.

This study contributes to the airline transportation industry literature, but it does have some limitations. Conclusions are based only on data from the United States, and other markets might have different characteristics. This issue can be circumvented by using other market data for validating the results. Another limitation is that some quality data are lacking, such as managerial capability, labor union, and leadership data, which might be critical factors influencing airline performance. Furthermore, future studies can be performed using other data mining techniques or MCDM methods, such as the random forest method, support vector machine, technique for order performance by similarity to ideal solution (TOPSIS) method, gray relations, AHP, or some combination with fuzzy theory for comparison. In summary, this study provides a new systematic approach for ensuring continuous improvement of financial and operational airline performance.

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