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# A fuzzy integral-based model for supplier evaluation and improvement

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ABSTRACT

Decisions related to supplier improvement and selection are inherently multiple criteria decision making (MCDM) problems and are strategically important to companies. Although efforts have been made to discover systematic methods to select the proper supplier, these efforts have assumed that the criteria are independent, which is not actually the case. Some studies that have treated the criteria as interdependent use additive models to obtain aggregate performance. We propose a novel fuzzy integral-based model that addresses the interdependence among the various criteria and employs the non-additive gap-weighted analysis. The structure of the relationships among the criteria and the criteria weights are developed using Decision Making Trial and Evaluation Laboratory (DEMATEL) combined with a fundamental concept of an analytic network process (ANP) called DANP. The fuzzy integral is then used to aggregate the gaps using the weights obtained from the DANP. The proposed model addresses the shortcomings of prior models and provides a more reasonable representation of the real world. The method is demonstrated using supplier evaluation and improvement data from a Taiwanese company.



## 1. Introduction

Supplier evaluation and improvement processes are the most significant variables in the effective management of globalization, as they improve organizations through the channels of high-quality products and customer satisfaction. The traditional approach has been to rank and select suppliers solely on the basis of price. However, moving from ranking/selection to selection/improvement decisions in the contemporary supply-chain network is complicated, as potential options for selection/improvement decisions are evaluated using multiple criteria. Therefore, supplier selection/improvement has become an MCDM problem that includes several tangible and intangible factors [3,54]. Recently, these criteria have become increasingly complex, interdependent, and dynamic as environmental, social, political, and customer satisfaction concerns have been added to the traditional factors of quality, delivery, cost, and service. Additionally, traditional MCDM methods have generally only employed an additive model to evaluate, rank, and/or select the alternatives. More important, and from a practical standpoint, solving the problem of criteria gaps (gaps between actual performance and aspiration levels) while incorporating a non-additive (or super-additive) framework to address interdependence and feedback problems is a current trend within the MCDM field. Kahneman and Tversky [23] developed the basic concept of non-additive (or super-additive) value-function aggregation in multi-criteria problems. This concept has led researchers to an important question on how

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these two concepts (non-additive value functions and aspiration levels) can be applied to real world inter-relationship (dependence and feedback) problems. This article contributes a novel, hybrid, fuzzy integral-based DANP (DEMATEL-based ANP) model for reducing the gaps between each dimension and criterion to reach a given aspiration level in real world inter-relationship problems.

Effective supplier selection/improvement demands robust analytical methods and tools that are applicable to the supplier decision and able to analyze multiple subjective and objective criteria [2]. A series of literature reviews has summarized the criteria and decision methods that have appeared in papers since the mid-1960s. For example, in an exhaustive review of 76 articles, Weber et al. [53] found that 47 articles address the involvement of more than one criterion. Two journal articles [10,59] reviewed the literature regarding supplier evaluation and improvement/selection models. Ho et al. [16] extended these reviews by surveying multi-criteria supplier evaluation and improvement/selection approaches through a literature review and a classification of international journal articles from 2000 to 2008. They concluded that only extensive, multi-criteria decision-making approaches have been proposed for supplier selection. The approaches include the analytic hierarchy process (AHP), analytic network process (ANP), data envelopment analysis (DEA), fuzzy set theory, genetic algorithms (GA), mathematical programming, the multi-attribute rating technique (i.e., gray relation, VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), technique for order preference by similarity to an ideal solution (TOPSIS), and their hybrids.

Prior studies have made significant contributions to supplier selection; however, they have assumed the criteria to be independent when modeling the supplier selection problem. In the real world, the criteria are seldom independent. In fact, the relationships between the criteria are all, to some extent, interactive and occasionally include dependence and feedback effects [20,36,46]. Others [19,27,30,18,29,12] have accounted for this interdependence (i.e., by using the ANP) but nonetheless employed additive models (i.e., VIKOR, gray relation or TOPSIS) to aggregate performances and weights. However, these methods are inconsistent with the assumption that the criteria are interdependent. A means of avoiding this inconsistency is to apply non-additive fuzzy integrals to integrate the interdependent performance values. In this study, we improve on prior research in three ways. First, the interdependent relationships between, and weights of, the criteria are constructed and calculated using DEMATEL and a fundamental concept of the ANP called DANP. This method can derive weights directly from the DEMATEL results and accommodate the different degrees of influence across dimensions. It also avoids the time-consuming process of performing pair-wise comparisons between criteria required in the original ANP analysis. Second, based on the concepts of VIKOR, the traditional relative good solution from the existing alternatives is replaced by the aspiration levels to avoid the "Choose the best among inferior choices/options/alternatives", i.e., avoid "Pick the best apple among a barrel of rotten apples" option. Third, a non-additive fuzzy integral is used to obtain influence weighted gaps that enable managers to better measure and understand the gaps between aspiration levels and actual levels and establish improvement priorities. Using this hybrid model, we can remedy the inconsistency in our prior studies [18,29] that assume interdependent criteria but apply additive models. This study may present the first model that integrates the concepts of a non-additive value function and interdependence with feedback effects in the supplier selection problems. Moreover, the emphasis in the MCDM field has shifted from ranking and selection when determining the most preferable approaches to performance improvement. Our model provides a systematic approach to identify the source of problems rather than addressing the systems of the problems. We used data from a Taiwanese company to demonstrate this model. This generic model can be easily extended to other industries to aid other types of firms in selecting their optimal suppliers.

## 2. A brief review of the existing literature

Over the last two decades, various decision-making methods have been proposed to address supplier evaluation and selection problems. Critical reviews have summarized the criteria and decision methods employed in the supplier selection process, for example, Ho et al. [16], De Boer et al. [9], Degraeve et al. [10] Wu et al. [55] and Weber et al. [54]. Based on prior studies, we categorize the methodologies used to analyze the supplier selection problem as follows: (1) multi-attribute decision-making, (2) mathematical programming models, (3) intelligent approaches, and (4) integrated approaches.

### *2.1. Multi-attribute decision-making (MADM)*

The most popular multi-attribute decision-making methods are the AHP and ANP. Shaw et al. [40] applied a fuzzy AHP to analyze a low carbon supply chain decision. The factors they considered are cost, quality, rejection percentage, late delivery percentage, green house gas emissions and demand. Bertolini et al. [3] used the AHP to select the best discount rate in defining a proposal for a public works contract. A hierarchical structure comprised of 31 criteria is reported to illustrate the performance and characteristics of the proposed technique. Chan and Kumar [4] developed a fuzzy AHP model to identify and discuss some of the important and critical decision criteria including risk factors for the development of an efficient system for global supplier selection. Although the AHP assumes independent criteria, other researchers applied the ANP to consider interdependent criteria when constructing their models. Vinodh et al. [51] proposed a fuzzy ANP approach for the supplier selection process. The study employed an Indian electronic switch manufacturing company as a case study to demonstrate the model. Hsu and Hu [17] presented an ANP approach to incorporate the issue of hazardous substance management (HSM) into supplier selection. The simple multi-attribute rating technique (SMART) is another MADM method. Barla [2] conducted a five-step approach based on SMART to evaluate and select suppliers for a glass manufacturing company. They used seven evaluative criteria where multiple sub-factors had to be considered. The subcontractor receiving the highest score, called the "total expected utilities", would be selected.

### 2.2. Mathematical programming models

Most authors used single objective techniques, such as linear, nonlinear integer, goal, or mixed-integer programming, in which one criterion, typically cost, is considered the objective function, while other criteria are considered constraints [32,44,15,52]. Conversely, some researchers applied multi-objective mathematical programming to this problem. For example, Wu et al. [56] proposed a fuzzy multi-objective programming model to select a supplier while accounting for risk factors. Their supply chain model included three levels and used simulated historical quantitative and qualitative data. Liao and Rittscher [26] developed a multi-objective supplier selection model under stochastic demand conditions. The stochastic supplier decision is made through the simultaneous consideration of the total cost, the quality rejection rate, the late delivery rate and the flexibility rate, including constraints on demand satisfaction and capacity. In addition to single or multiple objective programming, the DEA and its derivative methods were used by many authors to address supplier selection problems. Falagario et al. [13] developed a cross-efficiency DEA model for selecting the best supplier among the eligible candidates. The proposed technique allows for the evaluation of quantitative data related to vendor selection and retains the transparency aspects demanded by public procurement processes.

### 2.3. Intelligent approaches

There are examples [8,59] where intelligent systems such as an artificial neural network (ANN), evolutionary fuzzy systems, data-mining approaches, and expert systems tools have been used to evaluate the supplier selection process. Moghadam et al. [31] presented a hybrid intelligent algorithm based on push supply chain management that uses a fuzzy neural network and a genetic algorithm to forecast the rate of demand, determine material plans and select the optimal supplier. To incorporate the uncertain environment, a genetic algorithm based on bi-random simulation was designed by Xu and Ding [57] for solving a bi-random, multi-objective vendor selection problem.

### 2.4. Integrated approaches

Because the individual approaches contain limitations, numerous integrated approaches to supplier selection have been proposed in the last decade. Sevkli et al. [39] applied an integrated AHP–DEA approach to supplier selection. They used the AHP to derive local weights from a given pair-wise comparison matrix and aggregated local weights to yield overall weights. Each row and column of the matrix was assumed to be a decision-making unit (DMU) and an output. A dummy input that had a value of one for all DMUs was deployed in the DEA to calculate the efficiency scores of all suppliers. Amid et al. [1] used a weighted max–min fuzzy model to effectively address the vagueness of the input data and different criteria weights in a supplier selection problem. Kuo et al. [24] developed a green supplier selection model that combines the ANN and two multi-attribute decision analysis methods, the DEA and ANP. This model overcomes traditional DEA drawbacks, limitations of data accuracy and DMUs amount constraint.

Tzeng's research group [48,58] used the ANP combined with the DEMATEL (DANP) to weight the influence levels of the criteria. They then applied VIKOR to prioritize improvements in the performance of each alternative (such as service suppliers). However, they still used additive models to aggregate performance scores. Many other integrated approaches have been developed, including combining the ANP with goal programming [11], the ANN with GA [25], and the fuzzy AHP [4] and DEA with multi-objective programming [45].

Based on the above literature review, previous studies have generally assumed that the criteria are independent when establishing supplier evaluation models. A few authors have focused on the interdependence of the criteria when using the ANP, but they nonetheless applied additive models to aggregate performance values. Unlike previous studies, we propose a non-additive model combined with the measurement of gaps between observed aspired levels to make improvements and select a supplier, as described in the next section.

## 3. Proposed fuzzy integral-based integrated approach

In this section, we introduce the analytical processes of the hybrid model as illustrated in Fig. 1. As shown in the figure, a DEMATEL-based ANP is used to establish the structural relationship model and determine the criteria weights with dependence and feedback. In a complex system, all system criteria are either directly or indirectly mutually related. In such intricate systems, it is very difficult for a decision maker to obtain a specific objective/aspect and avoid interference from the rest of the system. This study uses the DEMATEL technique to determine the effect on each dimension and criterion. Subsequently, the DANP approach, a novel combination of the DEMATEL and ANP methods based on concepts developed by Saaty [38], was adopted to calculate the weights of the criteria. The concepts of VIKOR are applied to transform the performance values into gaps. Finally, we utilize a non-additive, fuzzy-integral model to aggregate the weighted gaps. As the DANP

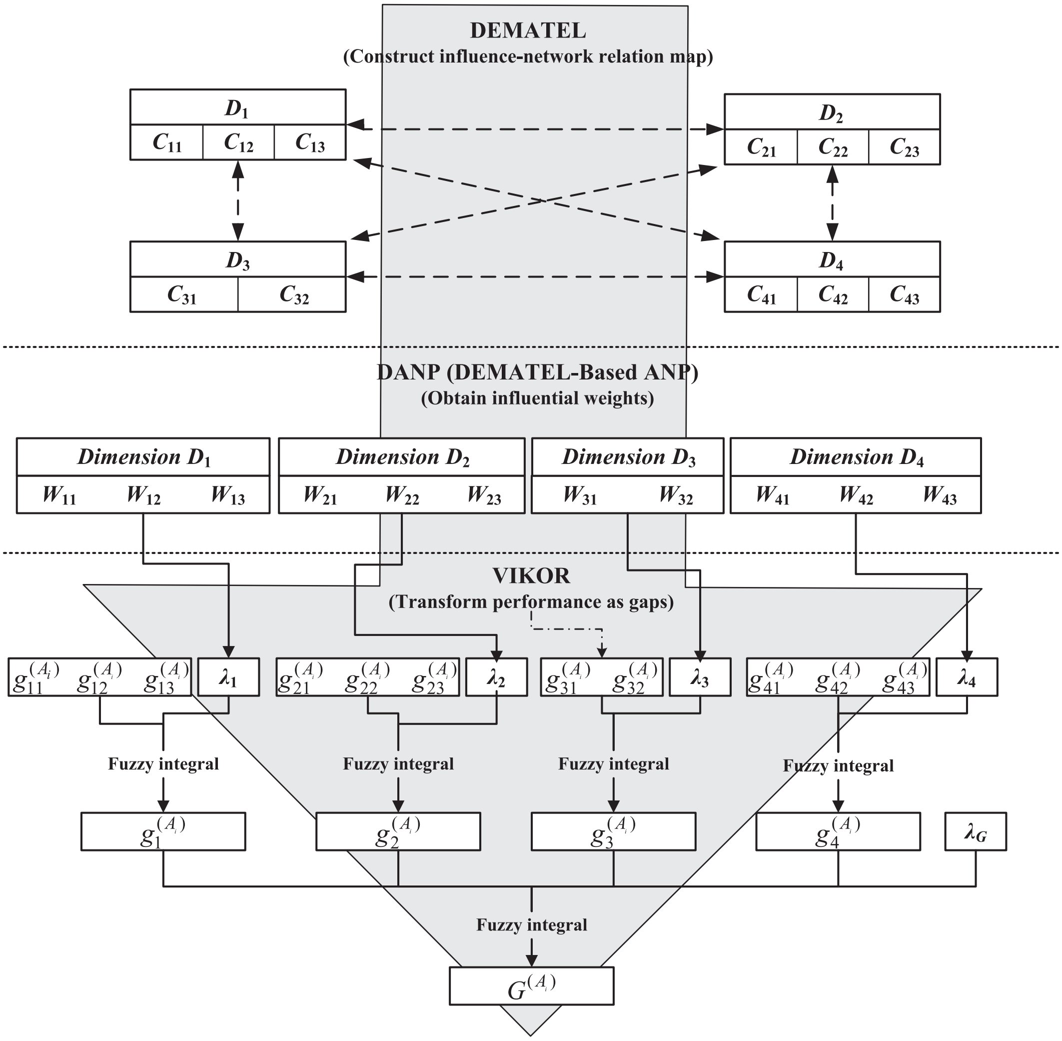



**Fig. 1.** Analysis processes.

method has been applied in many of our past studies [19,30,41], details of the procedures are illustrated in Appendix A. We will only stress the new concepts of the improved model here.

*3.1. Using the basic concepts of the VIKOR method to determine the gap values in the performance matrix*

In this study, we use the basic concepts of the VIKOR method to determine performance gap values. This article focuses on a method for constructing strategic systems to improve and reduce the gaps from existing performance values to achieve the aspiration/desired levels for each criterion. The decision makers then determine areas in need of improvement and select the best alternative to make decisions based on the new theoretical approach and apply these new hybrid methods to real cases with alternatives $A_1, A_2, \ldots, A_k, \ldots, A_m$. The performance score of alternative $A_k$ on the $j$th criterion is denoted as $f_{kj}$; $w_j$ is the relative influence weight of the $j$th criterion and can be obtained from the DANP where $j = 1, 2, \ldots, n$, and $n$ are the number of criteria. The VIKOR method was developed using the following traditional additive form of the $L_v$-metric [30]:

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

where $1 \leqslant v \leqslant \infty$; $k = 1, 2, \ldots, m$; and the influential weight $w_j$ is derived from the DANP. To formulate the ranking and gap ratio, measures $L_k^{v=1}$ and $L_k^{v=\infty}$ are used in the VIKOR method [50,35,33,34].

$$L_k^{v=1} = \sum_{j=1}^{n} [w_j(|f_j^* - f_{kj}|)/(|f_j^* - f_j^-|)] \tag{2}$$

$$L_k^{v=\infty} = \max_j\{(|f_j^* - f_{kj}|)/(|f_j^* - f_j^-|)|j = 1,2,\ldots,n\} \tag{3}$$

where we define $r_{kj} = (|f_j^* - f_{kj}|)/(|f_j^* - f_j^-|)$ as the gap ratio of alternative $k$ for criterion $j$. The compromise solution $\min_k L_k^v$ yields the synthesized/aggregated gap ratio that will also be minimized using Eq. (2), and $L_k^{v=\infty}$ indicates which alternative will be the improvement priority, that is, which one has the maximum gap ratio of the criteria in each dimension or criterion. We then select the best $f_j^*$ values as the aspiration levels and the worst $f_j^-$ values as the tolerable levels for all criteria functions, $j = 1, 2, \ldots, n$. In this study, we modify the traditional approach (suppose the $j$th function denotes benefits: $f_j^* = \max_k f_{kj}$ and $f_j^- = \min_k f_{kj}$) and shift the concept from the "ranking" or "selection" of the most preferable alternatives to the "improvement" of their performance levels to achieve the aspiration level for each dimension and criterion. Therefore, the $f_j^*$ and $f_j^-$ values can be set by decision makers such that $f_j^*$ is the aspiration level and $f_j^-$ is the worst value. For example, in questionnaires, we can use performance scores ranging from zero to 10 (from very dissatisfied or very bad ← 0, 1, 2, ..., 9, 10 → very satisfied or very good) expressed in natural language, wherein the aspiration level can be set at 10 and the worst value at zero. In this study, we set $f_j^* = 10$ as the aspiration level and $f_j^- = 0$ as the worst value, settings that differ from the traditional approach. This allows us to avoid "choosing the best among inferior options/alternatives (i.e., avoid picking the best apple from among a barrel of rotten apples)". However, in the real world, the rational, suitable aggregation operator is not additive. Rather, it is non-additive (also called super-additive), as explained below.

### 3.2. The λ fuzzy measure and fuzzy integral

Based on the weight of each criterion obtained from the DANP, we can combine the fuzzy measure and performance matrix to calculate the integrated performance for each alternative. Let $g_\lambda$ be a $\lambda$ fuzzy measure that is defined on a power set $P(x)$ for the finite set $X = \{x_1, x_2, \ldots, x_n\}$. The fuzzy measure has the following property [49]:

$$\begin{aligned} &\forall A, B \in P(X),\ A \cap B = \varnothing, \\ &g_\lambda(A \cup B) = g_\lambda(A) + g_\lambda(B) + \lambda g_\lambda(A) g_\lambda(B) \quad \text{for} -1 < \lambda < \infty \end{aligned} \tag{4}$$

The density of the fuzzy measure $g_i = g_\lambda(\{x_i\})$ can be obtained from questionnaire responses (thus $g_\lambda(\{x_i\}) = u(x_i^*, x_i^0)$. Suppose that you have a ground-service company that perfectly meets all of your criteria, and you would like this company's rating to serve as 1. Now suppose that this company only perfectly meets one criterion $x_i^*$ and is inferior with respect to other criteria. How would you rate this company? The local weights $(w_1, w_2, \ldots, w_n)$ can be obtained through the DANP. Next, we let the fuzzy measure weights be

$$(g_\lambda(\{x_1\}), g_\lambda(\{x_2\}), \ldots, g_\lambda(\{x_n\})) = q(w_1, w_2, \ldots, w_n) = (w_1 q, w_2 q, \ldots, w_n q), \tag{5}$$

where $q$ is the adjusted weight coefficient.

$$\begin{aligned} &g_\lambda(\{x_1, x_2, \ldots, x_n\}) = \sum_{i=1}^{n} g_\lambda(\{x_i\}) + \lambda \sum_{i=1, j>i}^{n} g_\lambda(\{x_i\}) g_\lambda(\{x_j\}) + \cdots + \lambda^{n-1} g_\lambda(\{x_1\}) g_\lambda(\{x_2\}) \cdots g_\lambda(\{x_n\}), \quad \text{where} \\ &\quad g_\lambda(X) = g_\lambda(\{x_1, x_2, \ldots, x_n\}) = 1 \end{aligned} \tag{6}$$

Based on the above properties, one of the three following situations will be realized for a specific case with two attributes, $x_1$ and $x_2$.

a. If $\lambda > 0$, the $g_\lambda(A \cup B) > g_\lambda(A) + g_\lambda(B)$, which implies that $x_1$ and $x_2$ have multiplicative effects in $\{A, B\}$.
b. If $\lambda = 0$, then $g_\lambda(A \cup B) = g_\lambda(A) + g_\lambda(B)$, which implies that $x_1$ and $x_2$ have additive effects in $\{A, B\}$.
c. If $\lambda < 0$, then $g_\lambda(A \cup B) < g_\lambda(A) + g_\lambda(B)$, which means that $x_1$ and $x_2$ have substitutive effects in $\{A, B\}$.

In our model, the performance values are replaced by gaps that are equal to the aspired levels minus the evaluated values with respect to each criterion. If we let h be a measurable set function (gap function) defined on the fuzzy measurable space and suppose that $h(x_1) \geqslant h(x_2) \geqslant \cdots \geqslant h(x_n)$, then the fuzzy integral of fuzzy measure $g(\cdot)$ with respect to $h(\cdot)$ can be defined as follows [22] and as shown in Fig. 2:

$$\begin{aligned} \int h\,dg &= h(x_n) g(H_n) + [h(x_{n-1}) - h(x_n)] g(H_{n-1}) + \cdots + [h(x_1) - h(x_2)] g(H_1) \\ &= h(x_n)[g(H_n) - g(H_{n-1})] + h(x_{n-1})[g(H_{n-1}) - g(H_{n-2})] + \cdots + h(x_1) g(H_1) \end{aligned} \tag{7}$$

where $H_1 = \{x_1\}$, $H_2 = \{x_1, x_2\}, \ldots, H_n = \{x_1, x_2, \ldots, x_n\} = X$.

The fuzzy integral defined in Eq. (7) is called the Choquet integral [43,22,42,5–7,28]. By using the fuzzy integral to formulate the original data, not only can fewer and more representative factors be extracted to describe the system but the interactions between attributes are also considered. Here we used $\int h\, dg = a_{kn}$ as the integrated weighted gaps of the cluster $C_n$ at alternative $k$.

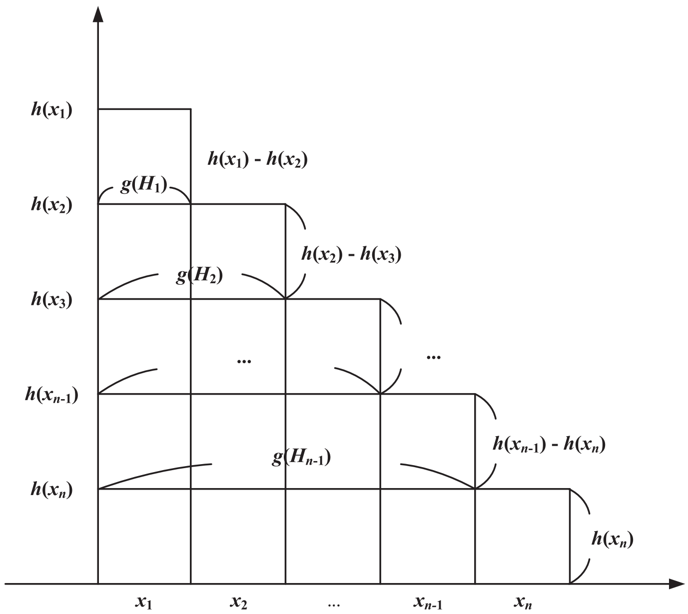



**Fig. 2.** Concept of fuzzy integral.

## 4. Empirical example using a real case

An empirical study on the selection and improvement of service suppliers in the airline industry is used in this section to illustrate the feasibility of the proposed methodology.

### *4.1. Problem descriptions*

Many decision-making methods have been proposed to address the supplier evaluation problem; however, the majority of prior works concern supplier selection in manufacturing industries, and few of them address service industries. Suppliers in service industries require greater collaboration than those in manufacturing industries because they perform numerous consecutive activities in a complete service process and to consistently impress customers, they have to employ management practices consistent with those of the outsourcing firm [14]. Therefore, it is necessary to consider the interdependencies between the outsourcing firm and the suppliers. Furthermore, the improvement and selection criteria in service industries are generally interrelated to a certain extent. Therefore, we use a service industry as the case study to validate our proposed model, reduce the gaps in the improvement criteria based on an influential network relationship map, and make a selection.

The model is developed and implemented using data from a Taiwanese airline that serves over 50 international destinations. To reduce manpower costs and improve service efficiency, the company sought to contract out its ground services at foreign destinations. Data from Bangkok, Thailand are selected for the case study because this is one of the most important destinations in this airline's flight network. Currently, five major ground-service companies ($A_1$ to $A_5$) are the potential alternatives to be selected as the airline's partner. The decision is strategic because its successful completion will have a significant bearing on the company's continued competitiveness.

### *4.2. Supplier improvement/selection criteria*

In any supplier improvement/selection activity, there are risks, such as potential structural and cultural incompatibilities. To ensure success, it is crucial that both firms and suppliers have a clear understanding of their similarities and differences and recognize mutually beneficial opportunities under cooperative arrangements. Because supplier improvement/selection is crucial, it is imperative for decision makers to devise, identify, and recognize effective supplier selection/improvement criteria and evaluate compatibility and feasibility issues prior to selecting any suppliers. Several issues are important for determining the optimal collaborator in this supplier improvement/selection process, including whether there have been favorable past associations between the potential suppliers, whether the national and corporate cultures of the suppliers are compatible, and whether trust exists among the suppliers' management teams. The supplier selection criteria are developed based on our review of the literature and a series of discussions with the case company's managers. This discussion with the industry helped us to classify the various decision-making criteria into four dimensions (or perspectives):

compatibility, risk, quality, and cost. These dimensions are then divided into various criteria, as indicated in Table 1. By examining these dimensions, we can avoid the pitfalls of classical supplier improvement/selection decisions where cost is used as the sole deciding factor.

### 4.3. Measuring the relationships between dimensions and criteria

Following the DANP procedures, as described in Appendix A (Step 4–8), the managers were asked to determine the degree of influence for each of the relationships among the criteria. The average initial direct-relation matrix $\boldsymbol{A}$ is an $11 \times 11$ matrix, obtained by pair-wise comparisons with respect to levels of influence and the direction of the relationships between dimensions, as shown in Table 2. As seen in matrix $\boldsymbol{A}$, the normalized direct-relation matrix $\boldsymbol{X}$ is calculated using Eqs. (A2) and (A3). Then, using Eq. (A4), the total-influence matrix $\boldsymbol{T}$ is derived, as indicated in Table 3. Additionally, by using Eqs. (A5) and (A6), the sum of the influence given $(r_i - s_i)$ and received $(r_i + s_i)$ for each dimension and criterion is shown in Table 4. It should be noted that the values on the left-hand side are the degrees of influence between dimensions, and the values on the right-hand side are the degrees of influence within criteria.

As seen in Table 4, risk $(r_i - s_i)$ has the largest positive value, as it is the most important dimension. Risk plays a major role in the evaluation system and has the most substantial impact on all other dimensions. As a result, managers perceive risk as a core consideration in any potential outsourcing activity. Compatibility has the highest value $(r_i + s_i)$, meaning that it can dramatically affect and be affected by other dimensions. Cost, however, has the lowest $(r_i + s_i)$ value, which implies that it is less significant than the other dimensions. In terms of degrees of influence among the criteria, these results indicate that managers believe that cost is the least influential factor when selecting a service supplier. This result seems to imply that service industries place greater emphasis on the level of quality provided and the potential risk than on the cost. The influential network-relationship can be visualized by drawing an influential network-relationship map (INRM) of the four dimensions and their subsystems as illustrated in Fig. 3. As the figure demonstrates, the "relationship," "loss of management control" and "knowledge skill" factors have the largest degrees of net influence under the subsystems of compatibility, risk and quality, respectively. The INRM can provide information on how to reduce the performance gaps in each dimension and provide assistance in identifying alternatives to reach the aspiration level.

The DANP method combines the DEMATEL with the ANP and conducts a survey of the case company to obtain indicators for the dynamic relationship. This information is used to construct an unweighted supermatrix indicating the degrees of importance among the relationships. Using the Eqs. (A10)–(A12), we can obtain the DEMATEL-based unweighted supermatrix as shown in Table 5. We also consider the impacts of various dimensions to create the weighted supermatrix. The weighted supermatrix (Table 6) is calculated from Eqs. (A8), (A14), and (A15) to reflect the degrees of influence exerted by the various dimensions. The limits of the supermatrix are used to obtain the weights of the various factors (global weight), and the weighted supermatrix is then raised to its limiting powers until the supermatrix has converged, as shown in Table 7. The DANP approach allows us to derive the local weights of the assessment factors at their respective hierarchical levels and global weights, which helps us to understand the absolute weights of individual criteria across all four perspectives. The properties are arranged according to the global weights. The purpose is to examine the primary criteria in the supplier selection decision to improve performance based on the INRM (Fig. 3). The results indicate that compatibility is the most

**Table 1**
Dimensions and criteria of the evaluating systems.

| Dimensions | Criteria | Explanations |
|---|---|---|
| Compatibility ($D_1$) | Relationship ($C_{11}$) | Includes shared risks and rewards, ensuring cooperation between the airline and ground service provider |
| | Flexibility ($C_{12}$) | Flexibility when dealing with abnormal situations, such as flight delays, overbooking, and incidents |
| | Information sharing ($C_{13}$) | Compatibility of computer systems and information-sharing, such as new information/ regulations at a destination airport |
| Quality ($D_2$) | Knowledge and skills ($C_{21}$) | Service provider's airplane maintenance facilities and their knowledge of manpower are essential |
| | Customer satisfaction ($C_{22}$) | Average customer's level of satisfaction regarding ground services, such as check-in and luggage handling |
| | On-time rate ($C_{23}$) | Ratio of airplanes delivered on time |
| Cost ($D_3$) | Cost saving ($C_{31}$) | Total cost of outsourcing activities |
| | Flexibility in billing ($C_{32}$) | Flexibility in billing and payment conditions, increasing goodwill between airlines and the service supplier |
| Risk ($D_4$) | Labor union ($C_{41}$) | Service outsourcing may be accompanied by the possibility of layoffs and disturbances within the airline. Supplier employee strikes could disrupt flight schedules |
| | Loss of management control ($C_{42}$) | Poor management of the service supplier may not provide adequate service and may cause potential flight safety problems |
| | Information security ($C_{43}$) | Mutual trust-based information sharing between the airline and the service supplier is necessary for both the continuance of the agreement and also for the security of confidential information |

**Table 2**
Initial direct influence matrix.

| $A$ | $C_{11}$ | $C_{12}$ | $C_{13}$ | $C_{21}$ | $C_{22}$ | $C_{23}$ | $C_{31}$ | $C_{32}$ | $C_{41}$ | $C_{42}$ | $C_{43}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $C_{11}$ | 0.0 | 2.5 | 3.3 | 1.3 | 1.9 | 1.5 | 3.0 | 3.3 | 3.2 | 3.1 | 2.9 |
| $C_{12}$ | 1.4 | 0.0 | 2.5 | 2.1 | 2.4 | 1.9 | 1.5 | 1.3 | 2.8 | 2.7 | 2.9 |
| $C_{13}$ | 3.3 | 2.4 | 0.0 | 2.8 | 1.5 | 1.8 | 0.8 | 0.7 | 3.2 | 2.9 | 2.8 |
| $C_{21}$ | 2.9 | 0.8 | 2.3 | 0.0 | 2.5 | 2.7 | 0.4 | 0.5 | 1.2 | 1.5 | 1.6 |
| $C_{22}$ | 3.2 | 2.2 | 2.1 | 2.5 | 0.0 | 1.1 | 0.7 | 0.9 | 0.5 | 0.8 | 0.6 |
| $C_{23}$ | 1.2 | 1.9 | 1.5 | 0.6 | 3.7 | 0.0 | 1.4 | 1.4 | 0.3 | 0.7 | 0.5 |
| $C_{31}$ | 3.1 | 1.3 | 1.5 | 0.5 | 0.8 | 1.3 | 0.0 | 2.7 | 1.8 | 1.3 | 1.1 |
| $C_{32}$ | 2.4 | 3.3 | 0.9 | 0.2 | 0.4 | 0.4 | 2.7 | 0.0 | 0.9 | 0.7 | 0.4 |
| $C_{41}$ | 2.8 | 2.5 | 2.3 | 1.7 | 2.3 | 3.1 | 0.5 | 0.4 | 0.0 | 3.3 | 1.8 |
| $C_{42}$ | 3.1 | 2.3 | 2.4 | 0.8 | 3.3 | 2.7 | 2.7 | 2.3 | 2.9 | 0.0 | 3.5 |
| $C_{43}$ | 2.2 | 1.6 | 3.2 | 1.3 | 0.9 | 1.3 | 1.1 | 1.0 | 1.4 | 2.8 | 0.0 |

*Note 1:* The scales 0, 1, 2, 3 and 4 represent the range from "no influence (0)" to "very high influence (4)", respondents by experts.

*Note 2:* $\frac{1}{n(n-1)}\sum_{i=1}^{n}\sum_{j=1}^{n}\frac{|d_{ij}^{p}-d_{ij}^{p-1}|}{d_{ij}^{p}}\times 100\% = 3.45\% < 5\%$, i.e., significant confidence is 96.55%, where $p = 16$ denotes the number of experts and $d_{ij}^{p}$ is the average influence of $i$ criterion on $j$; and $n$ denotes number of criteria, here $n = 11$ and $n \times n$ matrix.

**Table 3**
Total influence matrix of criteria.

| $T^C$ | $C_{11}$ | $C_{12}$ | $C_{13}$ | $C_{21}$ | $C_{22}$ | $C_{23}$ | $C_{31}$ | $C_{32}$ | $C_{41}$ | $C_{42}$ | $C_{43}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $C_{11}$ | 0.34 | 0.37 | 0.41 | 0.24 | 0.33 | 0.29 | 0.31 | 0.32 | 0.37 | 0.39 | 0.36 |
| $C_{12}$ | 0.33 | 0.23 | 0.34 | 0.24 | 0.31 | 0.27 | 0.22 | 0.21 | 0.31 | 0.33 | 0.32 |
| $C_{13}$ | 0.41 | 0.33 | 0.27 | 0.28 | 0.30 | 0.29 | 0.21 | 0.21 | 0.34 | 0.35 | 0.33 |
| $C_{21}$ | 0.32 | 0.21 | 0.28 | 0.13 | 0.27 | 0.25 | 0.15 | 0.15 | 0.21 | 0.23 | 0.22 |
| $C_{22}$ | 0.31 | 0.24 | 0.26 | 0.21 | 0.16 | 0.18 | 0.15 | 0.16 | 0.18 | 0.20 | 0.18 |
| $C_{23}$ | 0.21 | 0.21 | 0.20 | 0.13 | 0.26 | 0.12 | 0.15 | 0.15 | 0.14 | 0.16 | 0.14 |
| $C_{31}$ | 0.31 | 0.23 | 0.24 | 0.14 | 0.19 | 0.19 | 0.13 | 0.23 | 0.23 | 0.22 | 0.20 |
| $C_{32}$ | 0.25 | 0.26 | 0.19 | 0.11 | 0.15 | 0.14 | 0.21 | 0.11 | 0.17 | 0.17 | 0.15 |
| $C_{41}$ | 0.37 | 0.32 | 0.33 | 0.23 | 0.31 | 0.31 | 0.19 | 0.18 | 0.21 | 0.34 | 0.28 |
| $C_{42}$ | 0.44 | 0.36 | 0.38 | 0.22 | 0.37 | 0.33 | 0.30 | 0.28 | 0.35 | 0.27 | 0.37 |
| $C_{43}$ | 0.31 | 0.25 | 0.32 | 0.19 | 0.22 | 0.22 | 0.18 | 0.18 | 0.24 | 0.29 | 0.18 |

*Note:* The total influence matrix is obtained from Eqs. (A2)–(A4) as shown in Appendix.

**Table 4**
Sum of influences given $r_i$ and received $s_i$ on dimensions and criteria.

| $T^D$ | Dimensions | | | | $T^C$ | Criteria | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $r_i$ | $s_i$ | $r_i + s_i$ | $r_i - s_i$ | | $r_i$ | $s_i$ | $r_i + s_i$ | $r_i - s_i$ |
| $D_1$ | 1.21 | 1.18 | 2.39 | 0.04 | $C_{11}$ | 3.73 | 3.61 | 7.34 | 0.12 |
| | | | | | $C_{12}$ | 3.12 | 3.02 | 6.14 | 0.09 |
| | | | | | $C_{13}$ | 3.33 | 3.22 | 6.55 | 0.11 |
| $D_2$ | 0.78 | 0.89 | 1.67 | −0.11 | $C_{21}$ | 2.43 | 2.11 | 4.54 | 0.33 |
| | | | | | $C_{22}$ | 2.23 | 2.87 | 5.10 | −0.65 |
| | | | | | $C_{23}$ | 1.88 | 2.59 | 4.48 | −0.71 |
| $D_3$ | 0.76 | 0.79 | 1.54 | −0.03 | $C_{31}$ | 2.30 | 2.21 | 4.51 | 0.09 |
| | | | | | $C_{32}$ | 1.89 | 2.17 | 4.07 | −0.28 |
| $D_4$ | 1.11 | 1.00 | 2.12 | 0.11 | $C_{41}$ | 3.09 | 2.76 | 5.85 | 0.34 |
| | | | | | $C_{42}$ | 3.68 | 2.96 | 6.64 | 0.72 |
| | | | | | $C_{43}$ | 2.59 | 2.74 | 5.33 | −0.16 |

*Note:* The sum of influences $r_i$ and $s_i$ are calculated by Eqs. (A5) and (A6).

important dimension in terms of influence, and the relationship is the first priority in terms of the global weights. As noted above, the DEMATEL is combined with the ANP method to validate individual performance perspectives, the causal relationships among the criteria, and the influence weights of the respective criteria.

### *4.4. Integrated weighted gaps using the fuzzy integral method*

We first transform the performance values into the values representing the sizes of the gaps between actual and desired performance. Then, using the obtained global weights and gaps for each criterion and dimension, we synthesize the influence weights and gap values. In contrast to previous studies that only apply additive models (i.e., simple additive weight, VIKOR,

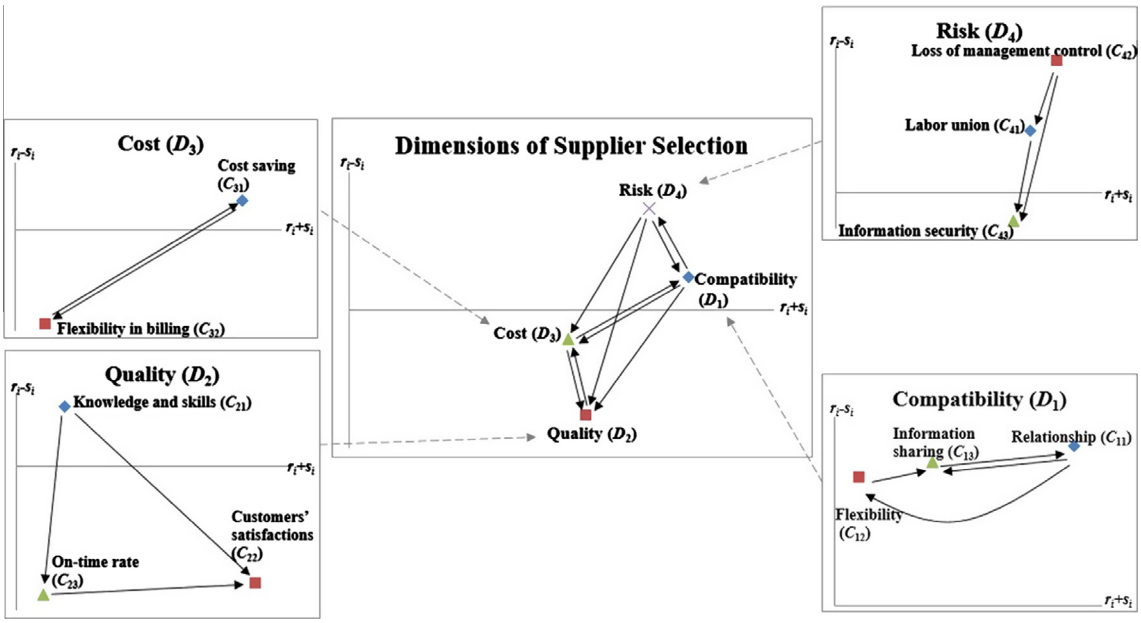



**Fig. 3.** Influential network-relationship map within systems.

**Table 5**
Un-weighted supermatrix of criteria.

| $W$ | $C_{11}$ | $C_{12}$ | $C_{13}$ | $C_{21}$ | $C_{22}$ | $C_{23}$ | $C_{31}$ | $C_{32}$ | $C_{41}$ | $C_{42}$ | $C_{43}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $C_{11}$ | 0.300 | 0.367 | 0.405 | 0.393 | 0.383 | 0.341 | 0.403 | 0.362 | 0.364 | 0.371 | 0.351 |
| $C_{12}$ | 0.332 | 0.258 | 0.327 | 0.263 | 0.301 | 0.335 | 0.290 | 0.372 | 0.312 | 0.306 | 0.286 |
| $C_{13}$ | 0.368 | 0.375 | 0.268 | 0.344 | 0.316 | 0.324 | 0.307 | 0.267 | 0.324 | 0.323 | 0.363 |
| $C_{21}$ | 0.280 | 0.293 | 0.321 | 0.201 | 0.377 | 0.249 | 0.263 | 0.274 | 0.267 | 0.242 | 0.297 |
| $C_{22}$ | 0.380 | 0.376 | 0.347 | 0.410 | 0.289 | 0.520 | 0.366 | 0.378 | 0.367 | 0.404 | 0.355 |
| $C_{23}$ | 0.340 | 0.331 | 0.332 | 0.389 | 0.334 | 0.231 | 0.371 | 0.347 | 0.366 | 0.354 | 0.348 |
| $C_{31}$ | 0.496 | 0.512 | 0.508 | 0.497 | 0.491 | 0.501 | 0.371 | 0.653 | 0.509 | 0.514 | 0.509 |
| $C_{32}$ | 0.504 | 0.488 | 0.492 | 0.503 | 0.509 | 0.499 | 0.629 | 0.347 | 0.491 | 0.486 | 0.491 |
| $C_{41}$ | 0.333 | 0.326 | 0.334 | 0.315 | 0.320 | 0.314 | 0.351 | 0.348 | 0.255 | 0.354 | 0.330 |
| $C_{42}$ | 0.346 | 0.342 | 0.343 | 0.350 | 0.355 | 0.361 | 0.340 | 0.346 | 0.410 | 0.273 | 0.411 |
| $C_{43}$ | 0.321 | 0.332 | 0.323 | 0.335 | 0.325 | 0.325 | 0.309 | 0.306 | 0.335 | 0.373 | 0.259 |

*Note:* The un-weighed supermatrix is derived by Eqs. (A10)–(A12).

**Table 6**
Weighted supermatrix $W^{\alpha}$.

| $W^{\alpha}$ | $C_{11}$ | $C_{12}$ | $C_{13}$ | $C_{21}$ | $C_{22}$ | $C_{23}$ | $C_{31}$ | $C_{32}$ | $C_{41}$ | $C_{42}$ | $C_{43}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $C_{11}$ | 0.084 | 0.102 | 0.113 | 0.126 | 0.123 | 0.110 | 0.131 | 0.118 | 0.112 | 0.114 | 0.108 |
| $C_{12}$ | 0.092 | 0.072 | 0.091 | 0.085 | 0.097 | 0.108 | 0.094 | 0.121 | 0.096 | 0.094 | 0.088 |
| $C_{13}$ | 0.103 | 0.105 | 0.075 | 0.111 | 0.101 | 0.104 | 0.100 | 0.087 | 0.100 | 0.100 | 0.112 |
| $C_{21}$ | 0.065 | 0.068 | 0.075 | 0.049 | 0.092 | 0.061 | 0.053 | 0.055 | 0.064 | 0.058 | 0.071 |
| $C_{22}$ | 0.089 | 0.088 | 0.081 | 0.100 | 0.071 | 0.127 | 0.074 | 0.076 | 0.088 | 0.097 | 0.085 |
| $C_{23}$ | 0.079 | 0.078 | 0.077 | 0.096 | 0.082 | 0.056 | 0.075 | 0.070 | 0.089 | 0.085 | 0.084 |
| $C_{31}$ | 0.101 | 0.104 | 0.103 | 0.097 | 0.096 | 0.098 | 0.083 | 0.145 | 0.100 | 0.101 | 0.100 |
| $C_{32}$ | 0.103 | 0.099 | 0.100 | 0.098 | 0.100 | 0.097 | 0.140 | 0.077 | 0.097 | 0.096 | 0.097 |
| $C_{41}$ | 0.095 | 0.093 | 0.095 | 0.075 | 0.076 | 0.075 | 0.088 | 0.087 | 0.065 | 0.090 | 0.084 |
| $C_{42}$ | 0.098 | 0.097 | 0.098 | 0.083 | 0.085 | 0.086 | 0.085 | 0.087 | 0.104 | 0.070 | 0.105 |
| $C_{43}$ | 0.091 | 0.094 | 0.092 | 0.080 | 0.077 | 0.078 | 0.077 | 0.077 | 0.085 | 0.095 | 0.066 |

*Note:* The weighted supermatrix is calculated by Eqs. (A8), (A14), and (A15).

TOPSIS, gray relation), we utilize fuzzy integrals to aggregate the weighted gaps. Because the criteria within the same dimension have interdependent relationships, their weighted gaps should be integrated rather than treated as individual values. Similarly, the integrated weighted gaps of the four dimensions should be further calculated with their final synthesized

**Table 7**
Influential weights of system factors.

| Dimensions | Local weights | Rankings | Criteria | Local weights | Rankings | Global weights |
|---|---|---|---|---|---|---|
| $D_1$ | 0.306 | 1 | $C_{11}$ | 0.367 | 1 | 0.112 |
| | | | $C_{12}$ | 0.310 | 3 | 0.095 |
| | | | $C_{13}$ | 0.324 | 2 | 0.099 |
| $D_2$ | 0.231 | 3 | $C_{21}$ | 0.281 | 3 | 0.065 |
| | | | $C_{22}$ | 0.379 | 1 | 0.088 |
| | | | $C_{23}$ | 0.340 | 2 | 0.079 |
| $D_3$ | 0.204 | 4 | $C_{31}$ | 0.506 | 1 | 0.103 |
| | | | $C_{32}$ | 0.494 | 2 | 0.101 |
| $D_4$ | 0.259 | 2 | $C_{41}$ | 0.327 | 2 | 0.085 |
| | | | $C_{42}$ | 0.351 | 1 | 0.091 |
| | | | $C_{43}$ | 0.322 | 3 | 0.083 |

*Note:* The global weights are derived by raising the weighted supermatrix to the limiting powers.

values. Through a survey questionnaire conducted by the case company's managers, fuzzy integral $\lambda$ values are obtained, which range from $-1$ to positive infinity $\infty$. These values represent the substitutive or multiplicative properties of the relationships among the criteria. There are substitutive effects among the risk attributes, and there is a multiplicative effect among compatibility, quality, and cost. The $\lambda$ values and the fuzzy measures $g(\cdot)$ are shown in Table 8. The fuzzy measures of each dimension and criterion are surveyed from the questionnaire. Using Eq. (5), we obtain the adjusted weight coefficient. Then, the $\lambda$ value is derived by solving the polynomial Eq. (6). Using the obtained $g(\cdot)$ and the original data (Appendix B, Table A1), we obtain the gap ratios ($r_{kj} = (|f_j^* - f_{kj}|)/(|f_j^* - f_j^-|)$ for alternatives $k = 1, 2, \ldots, m$ for each criterion (Table 9). The data in Table A1 represent the satisfaction levels for each ground-service company obtained from the managers of the case airline. The integrated weighted gaps of each potential supplier are then calculated as shown in Table 10. To illustrate the calculations, we use ground-service company $A_1$ as an example. Fig. 4(a) indicates how the integrated weighted gap of dimension 1 (compatibility) for company $A_1$ is obtained. Fig. 4(b) demonstrates how the total weighted gap is aggregated from the synthesized values of the four dimensions. The values for the other alternatives can be derived using the same methodology. According to our fuzzy integral model, $A_2$ has the smallest weighted gap and should, therefore, be selected, whereas the results from the conventional additive model (Table 9) differ, showing that $A_3$ is the best supplier. The results of a comparison of the two methods are illustrated in Table 11.

Table 11 shows the effect of the $\lambda$ values in the non-additive model. When $\lambda$ is equal to zero (additive model), the gap is not affected during the synthesization/aggregation processes. However, the gap will increase after synthesization/aggregation

**Table 8**
Fuzzy measure $g(\lambda)$ of each parameter and parameter combination.

| Fuzzy Measure $g(\cdot)$ | | | |
|---|---|---|---|
| *Supplier selection (evaluating systems)* $\lambda = -0.597$, $q = 1.358$ | | | |
| $g_\lambda(\{D_1\}) = 0.415$ | $g_\lambda(\{D_1, D_2\}) = 0.651$ | $g_\lambda(\{D_1, D_2, D_3\}) = 0.821$ | $g_\lambda(\{D_1, D_2, D_3, D_4\}) = 1$ |
| $g_\lambda(\{D_2\}) = 0.314$ | $g_\lambda(\{D_1, D_3\}) = 0.624$ | $g_\lambda(\{D_1, D_2, D_4\}) = 0.866$ | |
| $g_\lambda(\{D_3\}) = 0.277$ | $g_\lambda(\{D_1, D_4\}) = 0.680$ | $g_\lambda(\{D_1, D_3, D_4\}) = 0.844$ | |
| $g_\lambda(\{D_4\}) = 0.352$ | $g_\lambda(\{D_2, D_3\}) = 0.539$ | $g_\lambda(\{D_2, D_3, D_4\}) = 0.778$ | |
| | $g_\lambda(\{D_2, D_4\}) = 0.600$ | | |
| | $g_\lambda(\{D_3, D_4\}) = 0.571$ | | |
| *Compatibility ($D_1$)* $\lambda = 0.358$, $q = 0.900$ | | | |
| $g_\lambda(\{C_{11}\}) = 0.330$ | $g_\lambda(\{C_{11}, C_{12}\}) = 0.642$ | $g_\lambda(\{C_{11}, C_{12}, C_{13}\}) = 1$ | |
| $g_\lambda(\{C_{12}\}) = 0.279$ | $g_\lambda(\{C_{11}, C_{13}\}) = 0.656$ | | |
| $g_\lambda(\{C_{13}\}) = 0.291$ | $g_\lambda(\{C_{12}, C_{13}\}) = 0.599$ | | |
| *Quality ($D_2$)* $\lambda = 3.902$, $q = 0.539$ | | | |
| $g_\lambda(\{C_{21}\}) = 0.151$ | $g_\lambda(\{C_{21}, C_{22}\}) = 0.476$ | $g_\lambda(\{C_{21}, C_{22}, C_{23}\}) = 1$ | |
| $g_\lambda(\{C_{22}\}) = 0.204$ | $g_\lambda(\{C_{21}, C_{23}\}) = 0.443$ | | |
| $g_\lambda(\{C_{23}\}) = 0.183$ | $g_\lambda(\{C_{22}, C_{23}\}) = 0.533$ | | |
| *Cost ($D_3$)* $\lambda = 1.268$, $q = 0.798$ | | | |
| $g_\lambda(\{C_{31}\}) = 0.403$ | $g_\lambda(\{C_{31}, C_{32}\}) = 1$ | | |
| $g_\lambda(\{C_{33}\}) = 0.395$ | | | |
| *Risk ($D_4$)* $\lambda = -0.073$, $q = 1.025$ | | | |
| $g_\lambda(\{C_{41}\}) = 0.336$ | $g_\lambda(\{C_{41}, C_{42}\}) = 0.687$ | $g_\lambda(\{C_{41}, C_{42}, C_{43}\}) = 1$ | |
| $g_\lambda(\{C_{42}\}) = 0.360$ | $g_\lambda(\{C_{41}, C_{43}\}) = 0.657$ | | |
| $g_\lambda(\{C_{43}\}) = 0.330$ | $g_\lambda(\{C_{42}, C_{43}\}) = 0.681$ | | |

*Note 1:* The fuzzy measures for each dimension and criterion are obtained by questionnaire. The other fuzzy measures are calculated by Eq. (6).

**Table 9**
Gap ratio values of potential suppliers by SAW.

| Criteria | Weights (Global) | Weights (Local) | Alternative | | | | |
|---|---|---|---|---|---|---|---|
| | | | $A_1$ | $A_2$ | $A_3$ | $A_4$ | $A_5$ |
| Compatibility ($D_1$) | | **0.306** | **0.241** | **0.198** | **0.197** | **0.183** | **0.264** |
| Relationship ($C_{11}$) | 0.112 | 0.367 | 0.264 | 0.208 | 0.199 | 0.198 | 0.268 |
| Flexibility ($C_{12}$) | 0.095 | 0.310 | 0.214 | 0.211 | 0.198 | 0.176 | 0.264 |
| Information sharing ($C_{13}$) | 0.099 | 0.324 | 0.242 | 0.175 | 0.194 | 0.173 | 0.258 |
| Quality ($D_2$) | | **0.231** | **0.290** | **0.231** | **0.236** | **0.236** | **0.221** |
| Knowledge and skills ($C_{21}$) | 0.065 | 0.281 | 0.280 | 0.221 | 0.275 | 0.224 | 0.214 |
| Customer satisfaction ($C_{22}$) | 0.088 | 0.379 | 0.286 | 0.255 | 0.227 | 0.265 | 0.203 |
| On-time rate ($C_{23}$) | 0.079 | 0.340 | 0.302 | 0.213 | 0.213 | 0.214 | 0.246 |
| Cost ($D_3$) | | **0.204** | **0.243** | **0.306** | **0.320** | **0.343** | **0.268** |
| Cost saving ($C_{31}$) | 0.103 | 0.506 | 0.246 | 0.333 | 0.313 | 0.324 | 0.267 |
| Flexibility in billing ($C_{32}$) | 0.101 | 0.494 | 0.239 | 0.278 | 0.328 | 0.362 | 0.269 |
| Risk ($D_4$) | | **0.259** | **0.251** | **0.244** | **0.227** | **0.248** | **0.277** |
| Labor unions ($C_{41}$) | 0.085 | 0.327 | 0.257 | 0.292 | 0.214 | 0.219 | 0.275 |
| Loss of management control ($C_{42}$) | 0.091 | 0.351 | 0.255 | 0.208 | 0.218 | 0.248 | 0.288 |
| Information security ($C_{43}$) | 0.083 | 0.322 | 0.242 | 0.235 | 0.249 | 0.278 | 0.268 |
| Total Gap | | | **0.255** | **0.240** | **0.238** | **0.245** | **0.258** |
| (rank) | | | (4) | (2) | (1) | (3) | (5) |

*Note:* For example alternative $A_1$, $D_1$: (0.264 × 0.367) + (0.214 × 0.310) + (0.242 × 0.324) = 0.241, and total gap ratio = 0.241 × 0.306 + 0.290 × 0.231 + 0.243 × 0.204 + 0.251 × 0.259 = 0.255 (additive); the original data are shown in the Appendix, Table A1. The gap ratio is $r_{kj} = (|f_j^* - f_{kj}|)/(|f_j^* - f_j^-|)$ for alternatives $k = 1, 2, \ldots, m$ and criteria $j = 1, 2, \ldots, n$.

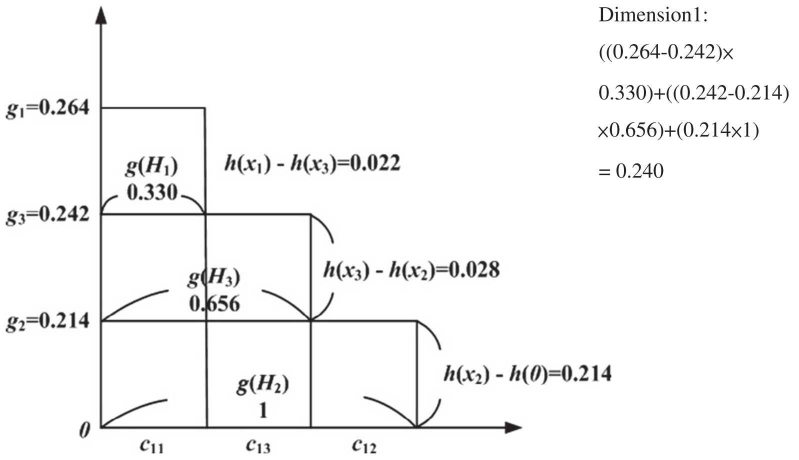
**Table 10**
Gap ratio values of potential suppliers by fuzzy integral.

| Criteria | Weights (local) | Alternative | | | | |
|---|---|---|---|---|---|---|
| | | $A_1$ | $A_2$ | $A_3$ | $A_4$ | $A_5$ |
| Compatibility ($D_1$) | **0.306** | **0.240** | **0.197** | **0.197** | **0.182** | **0.263** |
| Relationship ($C_{11}$) | 0.367 | 0.264 | 0.208 | 0.199 | 0.198 | 0.268 |
| Flexibility ($C_{12}$) | 0.310 | 0.214 | 0.211 | 0.198 | 0.176 | 0.264 |
| Information sharing ($C_{13}$) | 0.324 | 0.242 | 0.175 | 0.194 | 0.173 | 0.258 |
| Quality ($D_2$) | **0.231** | **0.286** | **0.224** | **0.227** | **0.227** | **0.214** |
| Knowledge and skills ($C_{21}$) | 0.281 | 0.280 | 0.221 | 0.275 | 0.224 | 0.214 |
| Customer satisfaction ($C_{22}$) | 0.379 | 0.286 | 0.255 | 0.227 | 0.265 | 0.203 |
| On-time rate ($C_{23}$) | 0.340 | 0.302 | 0.213 | 0.213 | 0.214 | 0.246 |
| Cost ($D_3$) | **0.204** | **0.242** | **0.300** | **0.319** | **0.339** | **0.268** |
| Cost saving ($C_{31}$) | 0.506 | 0.246 | 0.333 | 0.313 | 0.324 | 0.267 |
| Flexibility in billing ($C_{32}$) | 0.494 | 0.239 | 0.278 | 0.328 | 0.362 | 0.269 |
| Risk ($D_4$) | **0.259** | **0.252** | **0.245** | **0.227** | **0.249** | **0.277** |
| Labor unions ($C_{41}$) | 0.327 | 0.257 | 0.292 | 0.214 | 0.219 | 0.275 |
| Loss of management control ($C_{42}$) | 0.351 | 0.255 | 0.208 | 0.218 | 0.248 | 0.288 |
| Information security ($C_{43}$) | 0.322 | 0.242 | 0.235 | 0.249 | 0.278 | 0.268 |
| Total gap | – | **0.258** | **0.245** | **0.246** | **0.254** | **0.262** |
| (rank) | | (4) | (1) | (2) | (3) | (5) |

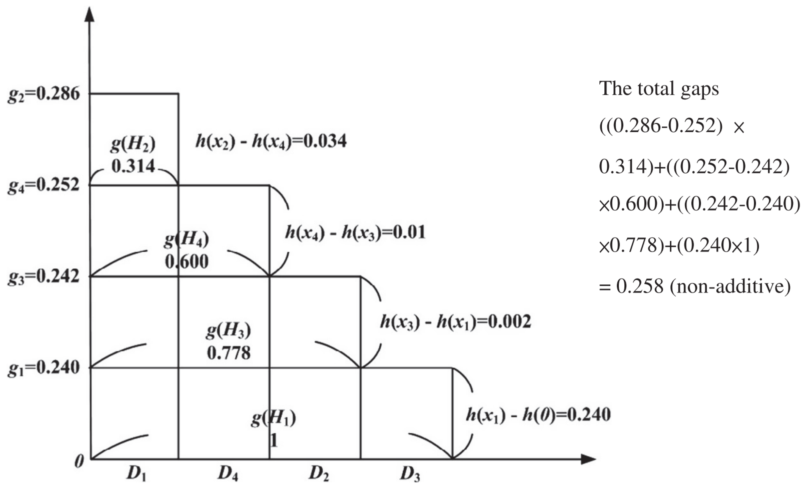
when the dimension exhibits a substitutive effect ($\lambda < 0$). Conversely, the multiplicative effect ($\lambda > 0$) will reduce the gap after synthesization/aggregation. The above phenomenon can be observed in our empirical example. The multiplicative effect on quality ($D_2$) reduces the gap of $A_3$, and the substitutive effect ($\lambda = -0.597$) within the dimensions increases the gap of $A_3$. The combined effects cause $A_3$ to fall from the leading position to second place and $A_2$ to shift from second place to first. Based on the substitutive or multiplicative effects within the dimensions and the INRM, we are able to derive some strategies for improvement. For example, for companies seeking to reduce the overall gap, controlling risk should be the most important task, as risk ranked first in the INRM and there is a substitutive effect among dimensions.

## 5. Discussion

According to the global weights (Table 7) of the improvement/selection criteria, the relationship (11.2%) is the most important criterion in supplier improvement/selection, followed by cost savings (10.3%) and billing flexibility (10.1%). However, based on the INRM (Fig. 3) and the influential degree analysis (Table 4), cost has the lowest $(r_i - s_i)$ value. These




(a) Fuzzy integral calculation for gap of dimension 1 in $A_1$




(b) Fuzzy integral calculation for total gap in $A_1$

**Fig. 4.** Illustration for the fuzzy integral calculation in $A_1$.

**Table 11**
Results comparison between non-additive and additive methods.

| | Dimension (additive/non-additive) | | | | |
|---|---|---|---|---|---|
| | $A_1$ | $A_2$ | $A_3$ | $A_4$ | $A_5$ |
| $D_1$ Compatibility<br>$\lambda = 0.358$ | 0.241/0.240<br>(-1%) | 0.198/0.179<br>(-1%) | 0.197/0.197<br>(0%) | 0.183/0.182<br>(0%) | 0.264/0.263<br>(0%) |
| $D_2$ Quality<br>$\lambda = 3.902$ | 0.290/0.286<br>(-1%) | 0.231/0.224<br>(-3%) | 0.236/0.227<br>(-4%) | 0.236/0.227<br>(-4%) | 0.221/0.214<br>(-3%) |
| $D_3$ Cost<br>$\lambda = 1.268$ | 0.243/0.242<br>(0%) | 0.306/0.300<br>(-2%) | 0.320/0.319<br>(-1%) | 0.343/0.339<br>(-1%) | 0.268/0.268<br>(0%) |
| $D_4$ Risk<br>$\lambda = -0.073$ | 0.251/0.252<br>(0%) | 0.244/0.245<br>(1%) | 0.227/0.227<br>(0%) | 0.248/0.249<br>(0%) | 0.277/0.277<br>(0%) |
| Total gaps<br>$\lambda = -0.597$ | 0.255/0.258<br>(1%) | 0.240/0.245<br>(2%) | 0.238/0.246<br>(3%) | 0.245/0.254<br>(4%) | 0.258/0.262<br>(1%) |

*Note:* Parenthesis represents the increased gap ratio%.

interesting results indicate that managers do not believe that cost influences the other criteria; however, they nonetheless consider cost an important factor when evaluating a supplier. Furthermore, these results do not necessarily suggest that less attention should be paid to risk factors. In fact, Table 4 indicates that risk has the highest degree of influence given $(r_i - s_i)$, and risk will influence the other dimensions more than they influence risk. In other words, risk considerations between the firm and its supplier will affect how the supplier fulfills other needs of the firm, such as compatibility and quality. However, compatibility has the highest value ($r_i + s_i$), which means it will affect the other dimensions and will also be dramatically affected by them. This is why compatibility has the greatest weight of all the dimensions. It should again be emphasized that the proposed model is capable of handling such interdependencies. Another advantage of the proposed model is that we can observe the directions of influence between dimensions through the INRM (Fig. 3) and provide improved supplier strategies. For example, the consideration of knowledge and skills has the highest value ($r_i - s_i$) in the quality subsystem, meaning that employees with superior knowledge skills could lead to increased service quality and avoid the possibility of delayed flights.

In the traditional evaluation system, relative performance values are generally applied to prioritize the alternatives. However, with our new approach, the decision maker sets an aspiration level (i.e., zero gaps in each dimension/criterion) as a benchmark. The performances are replaced by the weighted gaps that represent the direction of improvement between the alternative and the benchmark, which is more suitable in the contemporary competitive environment. As a consequence, the old model can only determine the gaps between a company and its leading competitors. Our model, however, not only helps companies to discover the gaps between current performance and aspiration levels, but it also provides an opportunity for them to outperform their leading competitors.

In the case study, if cost savings is the only criterion, it is obvious that $A_1$ should be selected. However, when multiple criteria and network relationships are included in the evaluation system and an additive model is used to synthesize the weighted gaps, the best service provider becomes $A_3$. This approach neglects the interdependence between performance levels, whereas our fuzzy integral-based model addresses this problem. Accordingly, our results reveal that $A_2$ is the best service provider. This non-additive model should provide more reasonable results than previous additive models because if there are network relationships between criteria, the performance levels should have the same effect.

Our model could also identify how alternatives can help a company reach its aspiration level for each criterion. For example, $A_5$ demonstrates poor performance for its on-time rate (the largest gap in the quality subsystem); however, it can reduce this gap by increasing its employees' knowledge and skills. This is because the knowledge and skills criterion has the highest net influence ($r_i - s_i$) in the INRM within the "quality" subsystem. Therefore, this model is capable of not only providing rankings and selections but also strategies for selecting improved alternatives to reach the desired aspiration levels, which is a new contribution.

It is worth noting that compared with the authors' previous study [18], which used the DANP and the additive models (i.e., gray relation analysis), the current study uses a non-additive model. Although the prior method captured the interdependency problem, the assumptions of the hybrid model are actually inconsistent. The DANP considers the criteria to be interdependent with the network relationship, but the gray relation method is basically an additive model that assumes that the criteria remain independent. Our current model corrects for this problem by using a non-additive model (i.e., fuzzy integrals). The empirical example shows that the effects of the information fusion are significant. Another similar study [29] was conducted using the ANP and fuzzy preference programming, but with the ANP method one needs to construct the network relationship in advance (by assumption). Our current model uses the DEMATEL to build the INRM. Fuzzy preference programming is used to cope with the diverse expert opinions rather than information fusion. This paper is the first attempt to consider information fusion and the INRM, and accordingly, it points to a new strategy for using MCDM to solve actual problems.

## 6. Conclusion and remarks

This paper analyzes supplier evaluation using a fuzzy integral-based model. We improve on previous models in several ways. First, the traditional models assume that the criteria are independently and hierarchically structured; however, in reality, decision problems are frequently characterized by interdependent criteria and dimensions and may even exhibit feedback-like effects. We applied the DEMATEL method to construct the network relationship. The DEMATEL-based ANP method is then used to derive the influence weights that, in a way, eliminate the time-consuming pair-wise comparisons in the original ANP. Second, relatively good solutions from the existing alternatives are replaced by aspiration levels to meet the demands of contemporary competitive markets. In this paper, VIKOR concepts are used to transform the performance levels into weighed gaps (the smaller the better) in each aspiration level. This enables a decision maker to reduce the gaps in alternatives to reach the aspiration levels and not simply a given performance level. Third, the emphasis on the MCDM applications has shifted from ranking and selection when determining the most preferable approaches to improving the performance of existing methods. The INRM identifies how and in which directions the criteria influence each other, which helps managers understand the root causes of performance issues and devise strategies for improvement. Fourth, information fusion techniques, including the fuzzy integral method, have been developed to aggregate the performance values. We utilized a fuzzy integral methodology to integrate the weights and gaps, which should be more applicable than conventional additive models. The empirical example indicates that the effect of the interdependencies among criteria is significant. We believe that the results of this application of our method are promising. Therefore, we conclude that the application of a fuzzy integral-based model to support decisions related to supplier selection can be fruitful.

Although the present study makes a significant contribution to the literature, it does have limitations. To obtain the non-additive effect, we applied the $\lambda$ fuzzy measure and assumed the $\lambda$ value of each criterion to be the same within each dimension. A different method or various $\lambda$ values could be possible for each criterion, which would better represent the real world by creating various operating environments. Although we developed an empirical evaluation tool, we occasionally were forced to spend a substantial amount of time explaining the questionnaire to respondents. Therefore, another avenue for improvement is the development of a more effective fuzzy measure. As an additional limitation, the conclusions drawn from our study are based on service industry data; thus, we explored only a portion of our model. Other cases in manufacturing could be used to test our model across different industries to draw comparisons, thereby providing greater insight into the interdependence and non-additive effects in supplier selection/improvement problems.

## Appendix A.

This section introduces the DANP method that constructs the interdependent structure and determines the weights of the criteria.

### A.1. DANP method based on DEMATEL

The DANP is a novel method that combines the original DEMATEL with the basic concepts of ANP. The method can be summarized as follows:

*Step 1:* Calculate the direct relation average matrix

Assuming that the levels 0, 1, 2, 3 and 4 represent the range from "no influence (0)" to "very high influence (4)", experts ask respondents to propose the degree of direct influence each perspective/criterion $i$ exerts on each perspective/criterion $j$, which is denoted $d_{ij}$, using the assumed levels. A direct relationship matrix is produced for each respondent, and an average matrix $\boldsymbol{A}$ is then derived from the mean of the same perspective/criteria in the various direct matrices for all respondents. The average matrix $\boldsymbol{A}$ is as follows:

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1j} & \cdots & a_{1n} \\ \vdots & & \vdots & & \vdots \\ a_{i1} & \cdots & a_{ij} & \cdots & a_{in} \\ \vdots & & \vdots & & \vdots \\ a_{n1} & \cdots & a_{nj} & \cdots & a_{nn} \end{bmatrix}. \tag{A1}$$

*Step 2:* Calculate the initial direct influence matrix

The initial direct influence matrix $\boldsymbol{X}$ can be obtained by normalizing the average matrix $\boldsymbol{A}$. In addition, the matrix $\boldsymbol{X}$ can be obtained through Eqs. (A2) and (A3), in which all principal diagonal criteria are equal to zero.

$$\boldsymbol{X} = s \cdot \boldsymbol{A} \tag{A2}$$

$$s = \min\left\{\frac{1}{\max_i \sum_{j=1}^{n} |d_{ij}|}, \frac{1}{\max_j \sum_{i=1}^{n} |d_{ij}|}\right\}. \tag{A3}$$

*Step 3:* Derive the total influence matrix

A continuous decrease of the indirect effects of criteria along the powers of $\boldsymbol{X}$, e.g., $\boldsymbol{X}^2, \boldsymbol{X}^3, \ldots, \boldsymbol{X}^h$ and $\lim_{h\to\infty}\boldsymbol{X}^h = [0]_{n\times n}$, where $\boldsymbol{X} = [x_{ij}]_{n\times n}, 0 \leqslant x_{ij} < 1, 0 < \sum_i x_{ij} \leqslant 1, 0 < \sum_j x_{ij} \leqslant 1$ and at least one column sum $\sum_j x_{ij}$ or one row sum $\sum_i x_{ij}$ equals 1. The total influence matrix $T$ is

$$\boldsymbol{T} = \boldsymbol{X} + \boldsymbol{X}^2 + \cdots + \boldsymbol{X}^h = \boldsymbol{X}(\boldsymbol{I} - \boldsymbol{X})^{-1}, \quad \text{when } \lim_{h\to\infty}\boldsymbol{X}^h = [0]_{n\times n} \tag{A4}$$

where $\boldsymbol{T} = [t_{ij}]_{n\times n}$, for $i, j = 1, 2, \ldots, n$ and $(\boldsymbol{I} - \boldsymbol{X})(\boldsymbol{I} - \boldsymbol{X})^{-1} = \boldsymbol{I}$. In addition, the method presents each row sum and column sum of the influence matrix $\boldsymbol{T} = [t_{ij}]_{n\times n}$ separately expressed as vector $\boldsymbol{r}$ and vector $\boldsymbol{s}$ using Eqs. (A5) and (A6) then

$$\boldsymbol{r} = (r_i)_{n\times 1} = \left[\sum_{j=1}^{n} t_{ij}\right]_{n\times 1}, \tag{A5}$$

$$\boldsymbol{s} = (s_j)_{n\times 1} = (s_j)'_{1\times n} = \left[\sum_{i=1}^{n} t_{ij}\right]'_{1\times n}, \tag{A6}$$

where the superscript $'$ denotes transpose; $r_i$ denotes the row sum of the $i$th row of matrix $\boldsymbol{T}$ and indicates the sum of the direct and indirect effects of perspective/criterion $i$ on the other perspectives/criteria. Similarly, $s_j$ denotes the column sum of the $j$th column of matrix $\boldsymbol{T}$ and indicates the sum of direct and indirect effects that perspective/criterion $j$ has received from the other perspectives/criteria. In addition, when $i = j$ (i.e., the sum of the row and column aggregates) $r_i + s_i$ provides an index of the strength of influences given and received, that is, $r_i + s_i$ indicates the extent to which criterion $i$ plays a central role in the problem. If $r_i - s_i$ is positive, then criterion $i$ affects the other criteria, and if $r_i - s_i$ is negative, then criterion $i$ is influenced by other criteria [47].

*Step 4:* Analyze the influence weights within dimensions

Each criterion $t_{ij}$ of influence matrix $\boldsymbol{T}$ can reveal network information regarding the degree of influence criterion $i$ has on criterion $j$, and the influential network relationship map (INRM) can thus be obtained. The influence matrix $\boldsymbol{T}$ can be divided into $T_D$ based on the perspectives (dimensions, or clusters) and $T_c$ based on the criteria, respectively.

$$\boldsymbol{T}_c = \begin{array}{cc} & \begin{array}{ccccc} D_1 & & D_j & & D_n \\ c_{11}\ldots c_{1m_1} & \cdots & c_{j1}\ldots c_{jm_j} & \cdots & c_{n1}\ldots c_{nm_n} \end{array} \\ \begin{array}{c} D_1 \begin{array}{c} c_{11} \\ c_{12} \\ \vdots \\ c_{1m_1} \end{array} \\ \vdots \\ D_i \begin{array}{c} c_{i1} \\ c_{i2} \\ \vdots \\ c_{im_i} \end{array} \\ \vdots \\ D_n \begin{array}{c} c_{n1} \\ c_{n2} \\ \vdots \\ c_{nm_n} \end{array} \end{array} & \begin{bmatrix} \boldsymbol{T}_c^{11} & \cdots & \boldsymbol{T}_c^{1j} & \cdots & \boldsymbol{T}_c^{1n} \\ \vdots & & \vdots & & \vdots \\ \boldsymbol{T}_c^{i1} & \cdots & \boldsymbol{T}_c^{ij} & \cdots & \boldsymbol{T}_c^{in} \\ \vdots & & \vdots & & \vdots \\ \boldsymbol{T}_c^{n1} & \cdots & \boldsymbol{T}_c^{nj} & \cdots & \boldsymbol{T}_c^{nn} \end{bmatrix} \end{array} \tag{A7}$$

$$\boldsymbol{T}_D = \begin{bmatrix} t_D^{11} & \cdots & t_D^{1j} & \cdots & t_D^{1n} \\ \vdots & & \vdots & & \vdots \\ t_D^{i1} & \cdots & t_D^{ij} & \cdots & t_D^{in} \\ \vdots & & \vdots & & \vdots \\ t_D^{n1} & \cdots & t_D^{nj} & \cdots & t_D^{nn} \end{bmatrix} \tag{A8}$$

The ANP weights, the general form of the AHP, are used here in the MCDM to remove the restriction of a hierarchical structure. The initial step in ANP procedures is to compare the criteria for the whole system in the form of an unweighted supermatrix through pair-wise comparisons. The weighted supermatrix is derived by transforming each column such that they will sum to unity (1.00) for a suitable Markov Chain process. This is achieved by dividing each element in a column by the number of clusters. Using this normalization method implies that each cluster has the same weight. However, employing the assumption that each cluster has equal weight to obtain the weighted supermatrix seems debatable in traditional ANP procedures because of the different degrees of influence among the criteria [36]. Therefore, in our new method, the DEMATEL technique is adopted to determine the degrees of influence for these criteria that are then applied to normalize the unweighted supermatrix in the ANP to suit the real world by using the normalized total-influential matrix $\boldsymbol{T}_D^{\alpha}$ of perspectives (dimensions) in weighting to avoid the equal weight problem. In the process $\boldsymbol{T}_c^{\alpha}$ can be obtained from a normalized $\boldsymbol{T}_c$ providing the total effect of the perspectives (or clusters) (Eq. (A9)), an example sub-matrix $\boldsymbol{T}_c^{12}$ (Eq. (A8)) from matrix $\boldsymbol{T}_c$ normalized into $\boldsymbol{T}_C^{\alpha 12}$ as is, for example, shown as Eqs. (A10) and (A11).

$$\boldsymbol{T}_c^{\alpha} = \begin{array}{cc} & \begin{array}{ccccc} D_1 & & D_j & & D_n \\ c_{11}\ldots c_{1m_1} & & c_{j1}\ldots c_{jm_j} & \cdots & c_{n1}\ldots c_{nm_n} \end{array} \\ \begin{array}{c} D_1 \begin{array}{c} c_{11} \\ c_{12} \\ \vdots \\ c_{1m_1} \end{array} \\ \vdots \\ D_i \begin{array}{c} c_{i1} \\ c_{i2} \\ \vdots \\ c_{im_i} \end{array} \\ \vdots \\ D_n \begin{array}{c} c_{n1} \\ c_{n2} \\ \vdots \\ c_{nm_n} \end{array} \end{array} & \begin{bmatrix} \boldsymbol{T}_c^{\alpha 11} & \cdots & \boldsymbol{T}_c^{\alpha 1j} & \cdots & \boldsymbol{T}_c^{\alpha 1n} \\ \vdots & & \vdots & & \vdots \\ \boldsymbol{T}_c^{\alpha i1} & \cdots & \boldsymbol{T}_c^{\alpha ij} & \cdots & \boldsymbol{T}_c^{\alpha in} \\ \vdots & & \vdots & & \vdots \\ \boldsymbol{T}_c^{\alpha n1} & \cdots & \boldsymbol{T}_c^{\alpha nj} & \cdots & \boldsymbol{T}_c^{\alpha nn} \end{bmatrix} \end{array} \tag{A9}$$

$$\boldsymbol{T}_c^{12} = \begin{array}{ccc} & \begin{array}{ccccc} c_{21} & \cdots & c_{2j} & \cdots & c_{2m_2} \end{array} & \\ \begin{array}{c} c_{11} \\ \vdots \\ c_{1i} \\ \vdots \\ c_{1m_1} \end{array} & \begin{bmatrix} \boxed{t_{11}^{12} \;\cdots\; t_{1j}^{12} \;\cdots\; t_{1m_2}^{12}} \\ \vdots \qquad \vdots \qquad \vdots \\ \boxed{t_{i1}^{12} \;\cdots\; t_{ij}^{12} \;\cdots\; t_{im_2}^{12}} \\ \vdots \qquad \vdots \qquad \vdots \\ \boxed{t_{m_1 1}^{12} \;\cdots\; t_{m_1 j}^{12} \;\cdots\; t_{m_1 m_2}^{12}} \end{bmatrix} & \begin{array}{l} \to t_1^{12} = \sum_{j=1}^{m_2} t_{1j}^{12} \\ \qquad \vdots \\ \to t_i^{12} = \sum_{j=1}^{m_2} t_{ij}^{12} \\ \qquad \vdots \\ \to t_{m_1}^{12} = \sum_{j=1}^{m_2} t_{m_1 j}^{12} \end{array} \end{array} \tag{A10}$$

where $t_i^{12} = \sum_{j=1}^{m_2} t_{ij}^{12}$, $i = 1, 2, \ldots, m_1$

$$T_c^{\alpha 12} = \begin{array}{c} \\ c_{11} \\ \vdots \\ c_{1i} \\ \vdots \\ c_{1m_1} \end{array} \begin{array}{c} \begin{array}{ccccc} c_{21} & \cdots & c_{2j} & \cdots & c_{2m_2} \end{array} \\ \begin{bmatrix} t_{11}^{12}/t_1^{12} & \cdots & t_{1j}^{12}/t_1^{12} & \cdots & t_{1m_2}^{12}/t_1^{12} \\ \vdots & & \vdots & & \vdots \\ t_{i1}^{12}/t_i^{12} & \cdots & t_{ij}^{12}/t_i^{12} & \cdots & t_{im_2}^{12}/t_i^{12} \\ \vdots & & \vdots & & \vdots \\ t_{m_1 1}^{12}/t_{m_1}^{12} & \cdots & t_{m_1 j}^{12}/t_{m_1}^{12} & \cdots & t_{m_1 m_2}^{12}/t_{m_1}^{12} \end{bmatrix} \end{array} = \begin{bmatrix} t_{11}^{\alpha 12} & \cdots & t_{1j}^{\alpha 12} & \cdots & t_{1m_2}^{\alpha 12} \\ \vdots & & \vdots & & \vdots \\ t_{i1}^{\alpha 12} & \cdots & t_{ij}^{\alpha 12} & \cdots & t_{im_2}^{\alpha 12} \\ \vdots & & \vdots & & \vdots \\ t_{m_1 1}^{\alpha 12} & \cdots & t_{m_1 j}^{\alpha 12} & \cdots & t_{m_1 m_2}^{\alpha 12} \end{bmatrix} \tag{A11}$$

*Step 5:* Construct an un-weighted supermatrix $\boldsymbol{W}$

In the traditional approach, the first step of the ANP is to use pair-wise comparisons with the criteria. For instance, you can use pairwise comparisons to form an un-weighted super-matrix by asking the following: "How important is a criterion relative to another criterion with respect to our interests or preferences?" It is very difficult to obtain consistent results from questionnaires in empirical settings. Therefore, we develop a new method, based on an original concept that allows parameter values to be matched in the total-influence matrix $\boldsymbol{T}_c$ to complete the relationships between perspectives (clusters) used in the DEMATEL technique. An unweighted supermatrix $\boldsymbol{W}$ can be easily obtained, as shown as Eq. (A12), by transposing the normalized influence matrix $\boldsymbol{T}_c^{\alpha}$ with respect to the perspectives (clusters).

$$\boldsymbol{W} = (\boldsymbol{T}_c^{\alpha})' = \begin{array}{cc} & \\ D_1 & \begin{array}{c} c_{11} \\ c_{12} \\ \vdots \\ c_{1m_1} \end{array} \\ \vdots & \\ D_j & \begin{array}{c} c_{j1} \\ c_{j2} \\ \vdots \\ c_{jm_j} \end{array} \\ \vdots & \\ D_n & \begin{array}{c} c_{n1} \\ c_{n2} \\ \vdots \\ c_{nm_n} \end{array} \end{array} \begin{array}{c} \begin{array}{ccccc} D_1 & & D_i & & D_n \\ c_{11}\ldots c_{1m_1} & & c_{i1}\ldots c_{im_i} & \cdots & c_{n1}\ldots c_{nm_n} \end{array} \\ \begin{bmatrix} \boldsymbol{W}^{11} & \cdots & \boldsymbol{W}^{i1} & \cdots & \boldsymbol{W}^{n1} \\ \vdots & & \vdots & & \vdots \\ \boldsymbol{W}^{1j} & \cdots & \boldsymbol{W}^{ij} & \cdots & \boldsymbol{W}^{nj} \\ \vdots & & \vdots & & \vdots \\ \boldsymbol{W}^{1n} & \cdots & \boldsymbol{W}^{in} & \cdots & \boldsymbol{W}^{nn} \end{bmatrix} \end{array} \tag{A12}$$

If the matrix $\boldsymbol{W}^{11}$ is blank or 0 as shown as Eq. (A13), this means that the matrix of the clusters or criteria is independent and lacks interdependence, and the other $\boldsymbol{W}^{nn}$ value are as above.

$$\boldsymbol{W}^{11} = \begin{array}{c} \\ \boldsymbol{c}_{11} \\ \vdots \\ \boldsymbol{c}_{1j} \\ \vdots \\ \boldsymbol{c}_{1m_1} \end{array} \begin{array}{c} \begin{array}{ccccc} \boldsymbol{c}_{11} & \cdots & \boldsymbol{c}_{1i} & \cdots & \boldsymbol{c}_{1m_1} \end{array} \\ \begin{bmatrix} t_{c11}^{\alpha 11} & \cdots & t_{ci1}^{\alpha 11} & \cdots & t_{cm_1 1}^{\alpha 11} \\ \vdots & & \vdots & & \vdots \\ t_{c1j}^{\alpha 11} & \cdots & t_{cij}^{\alpha 11} & \cdots & t_{cm_1 j}^{\alpha 11} \\ \vdots & & \vdots & & \vdots \\ t_{c1m_1}^{\alpha 11} & \cdots & t_{cim_1}^{\alpha 11} & \cdots & t_{cm_1 m_1}^{\alpha 11} \end{bmatrix} \end{array} \tag{A13}$$

*Step 6:* Normalize the total-influence matrix

We normalized the total-influence matrix $\boldsymbol{T}_D$ (Eq. (A8)) based on the perspectives and then obtained a new normalized influential matrix $\boldsymbol{T}_D^{\alpha}$ using the perspectives, as shown as Eq. (A14) (where $t_D^{\alpha ij} = t_D^{ij}/d_i$ and $d_i = \sum_{j=1}^{n} t_D^{ij}$).

$$\boldsymbol{T}_D^{\alpha} = \begin{bmatrix} t_D^{11}/d_1 & \cdots & t_D^{1j}/d_1 & \cdots & t_D^{1n}/d_1 \\ \vdots & & \vdots & & \vdots \\ t_D^{i1}/d_i & \cdots & t_D^{ij}/d_i & \cdots & t_D^{in}/d_i \\ \vdots & & \vdots & & \vdots \\ t_D^{n1}/d_n & \cdots & t_D^{nj}/d_n & \cdots & t_D^{nn}/d_n \end{bmatrix} = \begin{bmatrix} t_D^{\alpha 11} & \cdots & t_D^{\alpha 1j} & \cdots & t_D^{\alpha 1n} \\ \vdots & & \vdots & & \vdots \\ t_D^{\alpha i1} & \cdots & t_D^{\alpha ij} & \cdots & t_D^{\alpha in} \\ \vdots & & \vdots & & \vdots \\ t_D^{\alpha n1} & \cdots & t_D^{\alpha nj} & \cdots & t_D^{\alpha nn} \end{bmatrix} \tag{A14}$$

Let the normalized total-influence matrix $\boldsymbol{T}_D^{\alpha}$ complete the *un-weighted super-matrix to obtain the* weighted super-matrix as in the following step.

**Table A1**
Performance of each alternative.

| Criteria | Alternatives | | | | |
|---|---|---|---|---|---|
| | $A_1$ | $A_2$ | $A_3$ | $A_4$ | $A_5$ |
| Relationship ($C_{11}$) | 7.36 | 7.92 | 8.01 | 8.02 | 7.32 |
| Flexibility ($C_{12}$) | 7.86 | 7.89 | 8.02 | 8.24 | 7.36 |
| Information sharing ($C_{13}$) | 7.58 | 8.25 | 8.06 | 8.27 | 7.42 |
| Knowledge and skills ($C_{21}$) | 7.20 | 7.79 | 7.25 | 7.76 | 7.86 |
| Customer satisfaction ($C_{22}$) | 7.14 | 7.45 | 7.73 | 7.35 | 7.97 |
| On-time rate ($C_{23}$) | 6.98 | 7.87 | 7.87 | 7.86 | 7.54 |
| Cost saving ($C_{31}$) | 7.54 | 6.67 | 6.87 | 6.76 | 7.33 |
| Flexibility in billing ($C_{32}$) | 7.61 | 7.22 | 6.72 | 6.38 | 7.31 |
| Labor union ($C_{41}$) | 7.43 | 7.08 | 7.86 | 7.81 | 7.25 |
| Loss of management control ($C_{42}$) | 7.45 | 7.92 | 7.82 | 7.52 | 7.12 |
| Information security ($C_{43}$) | 7.58 | 7.65 | 7.51 | 7.22 | 7.32 |

*Step 7:* Obtain the weighted supermatrix

The normalization is used to derive the weighted super-matrix by transforming each column to sum exactly to unity. This step is similar to the Markov chain concept for ensuring that the sum of the probabilities of all states equals 1 [21]. In the traditional normalized method, each criterion in a column is divided by the number of perspectives (clusters) such that each column will sum to unity. Using this normalization method means each perspective (cluster) has the same weight. However, the effect of each perspective (cluster) on the other perspective (clusters) may be different. Therefore, it is not rational to use the assumption of equal weight for each perspective (cluster) to obtain the weighted super-matrix. Ou Yang et al. [36,37] proposed a hybrid method that employed the DEMATEL technique to solve this problem. First, the DEMATEL technique is used to derive the total influence matrix $\boldsymbol{T}_c$, and based on basic concept of ANP, an un-weighted super-matrix $\boldsymbol{W}$ of the perspectives can be obtained as in Eq. (A12). Then, the normalized total influence matrix $\boldsymbol{T}_D^\alpha$ of perspectives is represented as Eq. (A14). Thus, the weighted supermatrix $\boldsymbol{W}^\alpha$, for normalization, can be obtained as in Eq. (A15).

$$\boldsymbol{W}^\alpha = \boldsymbol{T}_D^\alpha \boldsymbol{W} = \begin{bmatrix} t_D^{\alpha 11} \times \boldsymbol{W}^{11} & \cdots & t_D^{\alpha i1} \times \boldsymbol{W}^{i1} & \cdots & t_D^{\alpha n1} \times \boldsymbol{W}^{n1} \\ \vdots & & \vdots & & \vdots \\ t_D^{\alpha 1j} \times \boldsymbol{W}^{1j} & \cdots & t_D^{\alpha ij} \times \boldsymbol{W}^{ij} & \cdots & t_D^{\alpha nj} \times \boldsymbol{W}^{nj} \\ \vdots & & \vdots & & \vdots \\ t_D^{\alpha 1n} \times \boldsymbol{W}^{1n} & \cdots & t_D^{\alpha in} \times \boldsymbol{W}^{in} & \cdots & t_D^{\alpha nn} \times \boldsymbol{W}^{nn} \end{bmatrix} \tag{A15}$$

*Step 8:* Limit the weighted super-matrix process for obtaining DANP influence weights

The weighted supermatrix can be raised to the limiting powers until the supermatrix has converged and become a long-term stable supermatrix to obtain the global priority vectors, called DANP (DEMATEL-based ANP) influence weights, such as $\lim_{g\to\infty}(\boldsymbol{W}^\alpha)^g$, where g represents any number of powers.

## Appendix B.

See Table A1.

## References


[1] A. Amid, S.H. Ghodsypour, C. O'Brien, A weighted max–min model for fuzzy multi-objective supplier selection in a supply chain, International Journal of Production Economics 131 (1) (2011) 139–145.
[2] S.B. Barla, A case study of supplier selection for lean supply by using a mathematical model, Logistics Information Management 16 (6) (2003) 451–459.
[3] M. Bertolini, M. Braglia, G. Carmignani, Application of the AHP methodology in making a proposal for a public work contract, International Journal of Project Management 24 (5) (2006) 422–430.
[4] F.T.S. Chan, N. Kumar, Global supplier development considering risk factors using fuzzy extended AHP-based approach, OMEGA 35 (4) (2007) 417–431.
[5] T.Y. Chen, J.C. Wang, G.H. Tzeng, Identification of general fuzzy measures by genetic algorithms based on partial information, IEEE Transactions on Systems, Man, and Cybernetics Part B: Cybernetics 30 (4) (2000) 517–528.
[6] H.K. Chiou, G.H. Tzeng, An extended approach of multicriteria optimization for MODM problems, in: Tanino et al. (Eds.), Multi-Objective Programming and Goal-Programming: Theory and Applications, Springer, 2003. pp. 111–116.
[7] H.K. Chiou, G.H. Tzeng, D.C. Cheng, Evaluating sustainable fishing development strategies using fuzzy MCDM approach, OMEGA 33 (3) (2005) 223–234.
[8] K.L. Choy, W.B. Lee, H. Lau, D. Lu, V. Lo, Design of an intelligent supplier relationship management system for new product development, International Journal of Computer Integrated Manufacturing 17 (8) (2004) 692–715.
[9] L. De Boer, E. Labro, P. Morlacchi, A review of methods supporting supplier selection, European Journal of Purchasing and Supply Management 7 (2) (2001) 75–89.
[10] Z. Degraeve, E. Labro, F. Roodhooft, An evaluation of supplier selection methods from a total cost of ownership perspective, European Journal of Operational Research 125 (1) (2000) 34–58.
[11] E.A. Demirtas, O. Ustun, Analytic network process and multi-period goal programming integration in purchasing decisions, Computer and Industrial Engineering 56 (2) (2009) 677–690.

[12] L. Dymova, P. Sevastjanov, A. Tikhonenko, An approach to generalization of fuzzy TOPSIS method, Information Sciences 238 (20) (2013) 149–162.
[13] M. Falagario, F. Sciancalepore, N. Costantino, R. Pietroforte, Using a DEA-cross efficiency approach in public procurement tenders, European Journal of Operational Research 218 (2) (2012) 523–529.
[14] B. Feng, Z.P. Fan, Y. Li, A decision method for supplier selection in multi-service outsourcing, International Journal of Production Economics 132 (2) (2011) 240–250.
[15] S.H. Ghodsypour, C. O'Brien, The total cost of logistics in supplier selection, under conditions of multiple sourcing, multiple criteria and capacity constraint, International Journal of Production Economics 73 (1) (2001) 15–27.
[16] W. Ho, X. Xu, P.K. Dey, Multi-criteria decision making approaches for supplier evaluation and selection: a literature review, European Journal of Operational Research 202 (1) (2010) 16–24.
[17] C.W. Hsu, A.H. Hu, Applying hazardous substance management to supplier selection using analytic network process, Journal of Cleaner Production 17 (2) (2009) 255–264.
[18] C.C. Hsu, J.J.H. Liou, Y.-C. Chuang, Integrating DANP and modified grey relation theory for the selection of an outsourcing provider, Expert Systems with Applications 40 (6) (2013) 2297–2304.
[19] C.Y. Huang, Y.H. Hung, G.H. Tzeng, Using hybrid MCDM methods to assess fuel cell technology for the next generation of hybrid power automobiles, Journal of Advanced Computational Intelligence and Intelligent Informatics 15 (4) (2010) 406–417.
[20] C.Y. Huang, J.Z. Shyu, G.H. Tzeng, Reconfiguring the innovation policy portfolios for Taiwan's SIP mall industry, Technovation 27 (12) (2007) 744–765.
[21] J.J. Huang, G.H. Tzeng, C.S. Ong, Multidimensional data in multidimensional scaling using the analytic network process, Pattern Recognition Letters 26 (6) (2005) 755–767.
[22] K. Ishii, M. Sugeno, A model of human evaluation process using fuzzy measure, International Journal of Man–Machine Studies 22 (1) (1985) 19–38.
[23] D. Kahneman, A. Tversky, On the psychology of prediction, Psychological Review 83 (4) (1973) 237–251.
[24] R.J. Kuo, Y.C. Wang, F.C. Tien, Integration of artificial neural network and MADA methods for green supplier selection, Journal of Cleaner Production 18 (12) (2010) 1161–1170.
[25] H.C.W. Lau, C.K.M. Lee, G.T.S. Ho, K.F. Pun, K.L. Choy, A performance benchmarking system to support supplier selection, International Journal of Business Performance Management 8 (2–3) (2006) 132–151.
[26] Z. Liao, J. Rittscher, A multi-objective supplier selection model under stochastic demand conditions, International Journal of Production Economics 105 (1) (2007) 150–159.
[27] J.J.H. Liou, Y.T. Chuang, Developing a hybrid multi-criteria model for selection of outsourcing providers, Expert Systems with Applications 37 (5) (2010) 3755–3761.
[28] J.J.H. Liou, G.H. Tzeng, A non-additive model for evaluating airline service quality, Journal of Air Transport Management 13 (3) (2007) 131–138.
[29] J.J.H. Liou, H.S. Wang, C.C. Hsu, S.L. Yin, A hybrid model for selection of an outsourcing provider, Applied Mathematical Modelling 35 (10) (2011) 5121–5133.
[30] C.H. Liu, G.H. Tzeng, M.H. Lee, Improving tourism policy implementation – the use of hybrid MCDM models, Tourism Management 33 (2) (2012) 239–488.
[31] M.R.S. Moghadam, A. Afsar, B. Sohrabi, Inventory lot-sizing with supplier selection using hybrid intelligent algorithm, Applied Soft Computing 8 (4) (2008) 1523–1529.
[32] W.L. Ng, An efficient and simple model for multiple criteria supplier selection problem, European Journal of Operational Research 186 (3) (2008) 1059–1067.
[33] S. Opricovic, G.H. Tzeng, Compromise solution by MCDM methods: a comparative analysis of VIKOR and TOPSIS, European Journal of Operational Research 156 (2) (2004) 445–455.
[34] S. Opricovic, G.H. Tzeng, Extended VIKOR method in comparison with outranking methods, European Journal of Operational Research 178 (2) (2007) 514–529.
[35] S. Opricovic, G.H. Tzeng, Multicriteria planning of post-earthquake sustainable reconstruction, Computer-Aided Civil and Infrastructure Engineering 17 (3) (2002) 211–220.
[36] Y.P. Ou Yang, H.M. Shieh, J.D. Leu, G.H. Tzeng, A novel hybrid MCDM model combined with DEMATEL and ANP with applications, International Journal of Operations Research 5 (3) (2008) 160–168.
[37] Y.P. Ou Yang, H.M. Shieh, G.H. Tzeng, A VIKOR technique based on DEMATEL and ANP for information security risk control assessment, Information Sciences 232 (2) (2013) 482–500.
[38] T.L. Saaty, Decision Making with Dependence and Feedback: Analytic Network Process, RWS Publications, 1996.
[39] M. Sevkli, S.C.L. Koh, S. Zaim, M. Demirbag, E. Tatoglu, An application of data envelopment analytic hierarchy process for supplier selection: a case study of BEKO in Turkey, International Journal of Production Research 45 (9) (2007) 1973–2003.
[40] K. Shaw, R. Shankar, S.S. Yadav, L.S. Thakur, Supplier selection using fuzzy ANP and fuzzy multi-objective linear programming for developing low carbon supply chain, Expert Systems with Applications 39 (9) (2012) 8182–8292.
[41] Y.C. Shen, G.T.R. Lin, G.H. Tzeng, Combined DEMATEL techniques with novel MCDM for the organic light emitting diode technology selection, Expert Systems with Applications 38 (3) (2011) 1468–1481.
[42] M. Sugeno, Y. Narukawa, T. Murofushi, Choquet integral and fuzzy measures on locally compact space, Fuzzy Sets and Systems 99 (2) (1998) 205–211.
[43] M. Sugeno, Theory of Fuzzy Integrals and its Applications, Tokyo, Japan: Ph.D. Thesis, Tokyo Institute of Technology, 1974.
[44] S. Talluri, R. Narasimhan, Vendor evaluation with performance variability: a max–min approach, European Journal of Operational Research 146 (3) (2003) 543–552.
[45] S. Talluri, S.K. Vickery, S. Narayanan, Optimization models for buyer–supplier negotiations, International Journal of Physical Distribution and Logistics Management 38 (7) (2008) 551–561.
[46] W.H. Tsai, W.C. Chou, Selecting management systems for sustainable development in SMEs: a novel hybrid model based on DEMATEL, ANP, and ZOGP, Expert Systems with Applications 36 (2) (2009) 1444–1458.
[47] G.H. Tzeng, C.H. Chiang, C.W. Li, Evaluating intertwined effects in e-learning programs: a novel hybrid MCDM model based on factor analysis and DEMATEL, Expert Systems with Applications 32 (4) (2007) 1028–1044.
[48] G.H. Tzeng, C.Y. Huang, Combined DEMATEL technique with hybrid MCDM methods for creating the aspired intelligent global manufacturing & logistics systems, Annals of Operations Research 197 (1) (2012) 159–190.
[49] G.H. Tzeng, J.J. Huang, Multiple Attribute Decision Making: Methods and Applications, CRC Press, Taylor & Francis Group, A Chapman & Hall Book, 2011.
[50] G.H. Tzeng, C.W. Lin, S. Opricovic, Multi-criteria analysis of alternative-fuel buses for public transportation, Energy Policy 33 (11) (2005) 1373–1383.
[51] S. Vinodh, R.A. Ramiya, S.G. Gautham, Application of fuzzy analytic network process for supplier selection in a manufacturing organisation, Expert Systems with Applications 38 (1) (2011) 272–280.
[52] V. Wadhwa, A.R. Ravindran, Vender selection in outsourcing, Computers and Operations Research 34 (12) (2007) 3725–3737.
[53] C.A. Weber, J.R. Current, W.C. Benton, Vendor selection criteria and methods, European Journal of Operational Research 50 (1) (1991) 2–18.
[54] C.A. Weber, J.R. Current, A. Desai, Non-cooperative negotiation strategies for vendor selection, European Journal of Operational Research 108 (1) (1998) 208–223.
[55] D. Wu, D.D. Wu, Y. Zhang, D. Olson, Supply chain outsourcing risk using an integrated stochastic-fuzzy optimization approach, Information Sciences 235 (20) (2013) 242–258.

[56] D.D. Wu, Y. Zhang, D. Wu, D.L. Olson, Fuzzy multi-objective programming for supplier selection and risk modeling: a possibility approach, European Journal of Operational Research 200 (3) (2010) 774–787.
[57] J. Xu, C. Ding, A class of chance constrained multiobjective linear programming with birandom coefficients and its application to vendors selection, International Journal of Production Economics 131 (2) (2011) 709–720.
[58] J.L. Yang, H.N. Chiu, G.H. Tzeng, R.H. Yeh, Vendor selection by integrated fuzzy MCDM techniques with independent and interdependent relationships, Information Sciences 178 (21) (2008) 4166–4183.
[59] M. Zeydan, C. Colpan, C. Cobanoğlu, A combined methodology for supplier selection and performance evaluation, Expert Systems with Applications 38 (3) (2011) 2741–2751.