IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 11 November 2023, accepted 24 December 2023, date of publication 1 January 2024,
date of current version 5 January 2024.

Digital Object Identifier 10.1109/ACCESS.2023.3348522

RESEARCH ARTICLE

Two Methods With Bidirectional Similarity for Optimal Selections of Supplier Portfolio and Supplier Substitute Based on TOPSIS and IFS

CHAO WANG[1], JIAXIN SHI[2], YANG YANG[2], AND RUI WANG[2]
[1]School of Information and Electrical Engineering, Hebei University of Engineering, Handan 056038, China
[2]School of Management Engineering and Business, Hebei University of Engineering, Handan 056038, China

Corresponding author: Jiaxin Shi (sjx0219@163.com)

This work was supported in part by the National Natural Science Foundation of China under Grant 11626079, in part by the Natural Science Foundation of Hebei Province under Grant A2020402013, and in part by the Humanities and Social Science Research Project of Hebei Education Department under Grant SQ2022085.

ABSTRACT The optimal selections of supplier portfolios and supplier substitutes are important research contents of the supplier selection problem. However, most of the existing supplier selection methods are based on the efficiency of indicator capability of supplier, the complementary capability (i.e., weak similarity) between suppliers for the supplier portfolio, and the substitution capabilities (i.e., strong similarity) of supplier substitutes for the best supplier may not be considered. Therefore, two new supplier selection models, namely TOPSIS-NS considering the negative influence of similarity for supplier portfolio selection and TOPSIS-PS considering the positive influence of similarity for supplier substitute selection, are proposed based on TOPSIS and intuitionistic fuzzy set (IFS). Firstly, the efficiency of indicator capability of supplier is expressed by the membership degree of IFS obtained by TOPSIS, while the similarity among suppliers is expressed by the nonmembership degree of IFS obtained by the concordance correlation coefficient. Then, the process of TOPSIS-NS for supplier portfolio selection is constructed based on the score function of IFS, and the supplier portfolio selected by TOPSIS-NS can have higher complementary capabilities. Furthermore, the process of TOPSIS-PS for supplier substitute selection is constructed based on the accuracy function of IFS, and the supplier substitute selected by TOPSIS-PS can have higher substitution capabilities. Finally, two illustrative examples for optimal selections of supplier portfolio and supplier substitute are given respectively, and the results show the superiority of TOPSIS-NS in supplier portfolio selection and TOPSIS-PS in supplier substitute selection.

INDEX TERMS Supplier portfolio selection, supplier substitute selection, similarity, MCDM, TOPSIS, intuitionistic fuzzy set.

I. INTRODUCTION

The optimal selections of supplier portfolio and supplier substitute, which can ensure the priority of the company in sustainable development, represent two significant portions of supplier selection. Without the suitable suppliers, it is impossible for a company to produce high-quality products at low cost [1]. Selecting not just the best alternative but two (or more) suppliers to reduce the supply risk and configuring the optimal supplier portfolio are the major requirements to be met in strategic supplier selection and are essential to achieve superior economic performance [2]. In addition, it is necessary to find a substitute for the best supplier, since even in the event of a supplier default, the buyer will be able to purchase from a substitute supplier [3]. Having qualified supplier substitutes to select from can increase bargain in power and production flexibility with maintaining production quality [4]. Therefore, selecting suitable suppliers as portfolio

The associate editor coordinating the review of this manuscript and approving it for publication was Francisco J. Garcia-Penalvo.

members or substitutes for the best supplier is crucial for the sustainable development and success of the company.

The main methods to deal with the supplier selection problems are mathematical programming [5], [6], intelligent techniques [7], [8], and multi-criteria decision-making (MCDM) [9], [10]. The mathematical planning model and intelligent technology model consider some comprehensive information and have good performance. However, these methods have high complexity, which are difficult to implement and find the optimal solution in practical applications. Furthermore, the MCDM methods result in a set of preferences, values, efficiency, or any other measurement criteria to rank suppliers and assist decision-makers [11], this is relatively simple and easy to implement the optimal supplier selection. Tronnebati et al. [12] reviewed a large number of research articles on supplier selection methods, and found the largest proportion of research articles used the MCDM methods. The popular MCDM methods are AHP, ANP, VIKOR, PROMETHEE, and TOPSIS, etc. Rahardjo et al. [13] combined DEMATEL-based on ANP with VIKOR, and ranking the available alternatives and selecting the best one can be accomplished using the VIKOR method, to simply solve the supplier selection problem and show the superiority and practicability of the MCDM model. Chen [14] combined entropy weight, AHP, TOPSIS into a suitable MCDM solution, and used the selection of building materials suppliers as an example to demonstrate that the TOPSIS method combination based on entropy AHP weight can effectively select suitable suppliers. Brans et al. [15] proposed the PROMETHEE method to solve multicriteria problems with a finite set of possible alternatives grouped in clusters or segments, and its extension for the portfolio selection presented by Brans et al. [16] (so called PROMETHEE V).

TOPSIS as a typical MCDM method was proposed by Hwang and Yoon [17], due to its simple process and ease of implementation for practitioners, many scholars have studied the application and improvement of TOPSIS method. Abootalebi et al. [18] proposed an improved TOPSIS method considering the nonunity of weights and the new defined relative closeness can be extended to group situation. Lo et al. [19] used TOPSIS to the evaluation of green suppliers, and the results showed that TOPSIS can effectively evaluate the performance of green suppliers. Selvachandran et al. [20] introduced two algorithms based on a modified TOPSIS approach and a weighted aggregation operator approach, and pplied in two MCDM problems involving supplier selection and the evaluation of supplier performance.

But these scholars did not consider using the TOPSIS method to solve supplier selection problems, the TOPSIS method ignores the bidirectional influence of similarity (positive similarity or negative similarity) among suppliers. When selecting a supplier portfolio, the supplier portfolio is obtained based on the ranking results of TOPSIS, which this ignores the negative influence of similarity among suppliers, and leads to the high similarity among suppliers of the optimal portfolio determined by TOPSIS. The higher similarity among suppliers means that they have the proximity of indicator capability, which results in low complementarity in selected supplier portfolio. Then, when selecting a substitute for the best supplier, a supplier with a high similarity to the best supplier should be perceived as more desirable and more likely to be selected as a substitute [21], i.e., substitutes with high similarity to the best suppliers have higher substitution capabilities. While the TOPSIS method selects the second-ranked supplier as a substitute for the best supplier, which this ignores the positive influence of similarity among suppliers, and leads to the selected supplier substitute may not necessarily have high similarity to the best supplier. Therefore, whether selecting supplier portfolio or supplier substitute, the influence of similarity among suppliers should be considered. In order to solve the drawbacks of the above two supplier selection situations, intuitionistic fuzzy sets (IFS) [22] is introduced in this paper.

IFS as an extension of Zadeh's fuzzy set [23] was introduced by Atanssov [22], which is incorporated by the membership degree μ and the nonmembership degree ν, where the membership degree μ and the nonmembership degree ν satisfy $0 \leq \mu + \nu \leq 1$. Since it was proposed, the IFS has drawn tremendous attention from researchers [24], [25], [26]. In this paper, two new supplier selection models, namely TOPSIS-NS considering the negative influence of similarity for supplier portfolio selection and TOPSIS-PS considering the positive influence of similarity for supplier substitute selection, are introduced to comprehensively select suppliers. The membership degree μ obtained by TOPIS is given to describe the indicator capability of suppliers, while the nonmembership degree ν obtained by the concordance correlation coefficient is given to describe the similarity among suppliers. When selecting supplier portfolio, it comprehensively selects the supplier portfolio by the score function of IFS. When selecting substitute for the best supplier, it comprehensively selects the supplier substitute by the accuracy function of IFS. Compared with TOPSIS, the TOPSIS-NS and the TOPSIS-PS consider the similarity among suppliers, the TOPSIS-NS is more suitable for supplier portfolio selection and the TOPSIS-PS for supplier substitute selection.

The rest of the paper is organized as follows: The preliminary of steps of TOPSIS, the intuitionistic fuzzy set, and the complementarity capability are provided in Section II. Two modified TOPSIS methods are introduced in Section III. Two Illustrative examples to demonstrate the feasibility of TOPSIS-NS in supplier portfolio selection and TOPSIS-PS in supplier substitute selection are provided in Section IV. Comparative analysis to show the superiority of the TOPSIS-NS in selecting supplier portfolios and the TOPSIS-PS in selecting supplier substitutes are provided in Section V. Finally, the conclusions are provided in Section VI.

II. PRELIMINARIES

A. TOPSIS

The steps of the TOPSIS is as follows:

Let $G = \{G_1, \cdots, G_i, \cdots, G_m\}$ be a set of alternatives, and $C = \{C_1, \cdots, C_k, \cdots, C_n\}$ be a set of evaluation indicators, the x_{ik} represents the value of the evaluation indicator C_k for the alternative G_i. The initialization evaluation matrix X is given by:

$$X = (x_{ik})_{m\times n} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}, \tag{1}$$

Step 1: Standardized evaluation matrix. In order to eliminate the influence of different dimensions of indicators on the decision-making, the standardized formula is given by:

$$r_{ik} = \frac{x_{ik}}{\sqrt{\sum_{j=1}^{m} x_{ik}^2}}, i = 1, \cdots, m; k = 1, \cdots, n, \tag{2}$$

and the normalized decision matrix R is shown as follows:

$$R = (r_{ik})_{m\times n} = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix}, \tag{3}$$

where r_{ik} is the normalized value of the evaluation indicator C_k for the alternative G_i.

Step 2: Establish weighted normalized decision matrix based on evaluation indicator weight ω_k and normalized decision matrix R by:

$$V = (v_{ik})_{m\times n} = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1n} \\ v_{21} & v_{22} & \cdots & v_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ v_{m1} & v_{m2} & \cdots & v_{mn} \end{bmatrix}, \tag{4}$$

where $v_{ik} = \omega_k r_{ik}$, the ω_k is the weight of evaluation indicator C_k,

Step 3: Determine the positive ideal solution (PIS) and the negative ideal solution (NIS):

$$\begin{aligned} S^+ &= \{v_1^+, \cdots, v_k^+, \cdots, v_m^+\} \\ &= \left\{(\max_k v_k | k \in n^+), (\min_k v_k | k \in n^-)\right\}, \end{aligned} \tag{5}$$

$$\begin{aligned} S^- &= \{v_1^-, \cdots, v_k^-, \cdots, v_m^-\} \\ &= \left\{(\min_k v_k | k \in n^+), (\max_k v_k | k \in n^-)\right\}, \end{aligned} \tag{6}$$

where n^+ is the set of benefit indicators and n^- is the set of cost indicators.

Step 4: Calculate the distance between each alternative to the PIS and the NIS:

$$d_i^+ = \sqrt{\sum_{k=1}^{n} (v_{ik} - v_k^+)^2}, i = 1, \cdots, m; k = 1, \cdots, n, \tag{7}$$

$$d_i^- = \sqrt{\sum_{k=1}^{n} (v_{ik} - v_k^-)^2}, i = 1, \cdots, m; k = 1, \cdots, n, \tag{8}$$

where d_i^+ represents the distance between the alternative G_i and the PIS, and d_i^- represents the distance between the alternative G_i and the NIS.

Step 5: Calculate the closeness coefficient of each alternative.

$$C_i = \frac{d_i^-}{d_i^+ + d_i^-}, i = 1, \cdots, m. \tag{9}$$

where $0 \le C_i \le 1$. Based on the closeness coefficient of the alternatives, the alternatives are sorted in descending order. Furthermore, the alternative with the highest closeness coefficient (C_i) is first selected.

B. INTUITIONISTIC FUZZY SET

IFS was introduced by Atanssov [22] as an extension of Zadeh's fuzzy set [23]. IFSs are defined as follows:

An intuitionistic fuzzy set A on a universe U is defined as follows:

$$A = \{\langle u, \mu_A(u), \nu_A(u)\rangle \,| u \in U\}, \tag{10}$$

where the functions $\mu_A : U \to [0, 1]$ and $\nu_A : U \to [0, 1]$ define membership degree and nonmembership degree of the element $u \in U$ in A, respectively. For every $u \in U$:

$$0 \le \mu_A(u) + \nu_A(u) \le 1, \ u \in U. \tag{11}$$

For convenience, $\alpha = (\mu_\alpha, \nu_\alpha)$ denotes an intuitionistic fuzzy number. The score value of the intuitionistic fuzzy number α is directly related to the difference between its membership degree μ_α and nonmembership degree ν_α. For given intuitionistic fuzzy number (μ_α, ν_α), it can be measured by a score function $s(\alpha)$ [27]:

$$s(\alpha) = \mu_\alpha - \nu_\alpha. \tag{12}$$

The larger the $s(\alpha)$ is, the larger the intuition fuzzy number α is. In particular, if $s(\alpha) = 1$, the α takes the maximum value (1,0); if $s(\alpha) = -1$, the α takes the minimum value (0, 1).

In addition, Hong and Choi added the following accuracy function $h(\alpha)$ [28]:

$$h(\alpha) = \mu_\alpha + \nu_\alpha. \tag{13}$$

The h is the accuracy function of α, and the $h(\alpha)$ is the accuracy degree of α. The larger the $h(\alpha)$ is, the higher the accuracy degree of the intuition fuzzy number α is.

TABLE 1. The normalized values of evaluation indicators, the closeness coefficients (C_i) and the ranking for the three suppliers.

Suppliers	Evaluation indicators			closeness coefficients (C_i)	Ranking
	C_1	C_2	C_3		
G_1	0.6	0.7	0.4	0.39	3
G_2	0.5	0.9	0.5	0.59	1
G_3	0.8	0.6	0.3	0.41	2

TABLE 2. The normalized values of evaluation indicators for the suppliers.

Alternatives	C_1	C_2	C_3	C_3
G	0.3	0.5	0.4	0.8
N_1	0.4	0.6	0.3	0.7
N_2	0.6	0.7	0.1	0.6

C. COMPLEMENTARY CAPABILITY

The supplier portfolio should be composed of supplier members with complementary capabilities. Therefore, the complementary capability is proposed to measure the degree of complementarity of supplier portfolio [29].

Let $G = \{G_1, \cdots, G_i, \cdots, G_m\}$ be a set of suppliers, let $C = \{C_1, \cdots, C_k, \cdots, C_n\}$ be a set of evaluation indicators. Then, the complementary capability $CC(i,j)$ [29] between the supplier G_i and the supplier G_j is defined by:

$$CC(i,j) = \sqrt{\sum_{k=1}^{n}\left(\frac{G_i(k) - G_j(k)}{C(k)_{\max}}\right)^2}, \tag{14}$$

where $G_i(k)$ and $G_j(k)$ represent the values of the evaluation indicator C_k for the supplier G_i and the supplier G_i, respectively. The $C(k)_{max}$ represents the maximum evaluation indicator value C_k. Then, the complementary capability $CC(N)$ of the supplier portfolio N is defined by:

$$CC\,(N) = \frac{1}{2}\sum_{i=1}^{n}\sum_{\substack{j=1\\ j\neq i}}^{n} CC\,(i,j). \tag{15}$$

III. METHODOLOGY

A. THE MEMBERSHIP DEGREE OF IFS BASED ON TOPSIS

Let $G = \{G_1, \cdots, G_i, \cdots, G_m\}$ be a set of suppliers. The indicator capability of supplier G_i is the closeness coefficient C_i of the supplier G_i obtained by TOPSIS, which is denoted by the membership degree of IFS:

$$\mu_i = C_i, \tag{16}$$

where $0 \leq C_i \leq 1$.

Example 1. Let $G = \{G_1, G_2, G_3, G_4\}$ be a set of suppliers. Suppose the normalized values of evaluation indicators, the closeness coefficients (C_i) and the ranking for the three suppliers are shown in Table 1. Hence, the membership degree μ of suppliers can be calculated by Equation (16).

$$\begin{aligned}\mu_1 &= C_1 = 0.39,\\ \mu_2 &= C_2 = 0.59,\\ \mu_3 &= C_3 = 0.41.\end{aligned} \tag{17}$$

B. THE NONMEMBERSHIP DEGREE OF IFS BASED ON CONCORDANCE CORRELATION COEFFICIENT

1) THE CONCORDANCE CORRELATION COEFFICIENT OF SUPPLIERS

Let $G = \{G_1, \cdots, G_i, \cdots, G_m\}$ be a set of suppliers, let $C = \{C_1, \cdots, C_k, \cdots, C_n\}$ be a set of evaluation indicators. The correlation and absolute interpolation between the supplier G_i and the supplier G_j is represented by the concordance correlation coefficient ζ_{ij} [30], which is given by:

$$\rho_{ij} = \frac{\sum_{k=1}^{n}(r_{ik} - \bar{r}_i)(r_{jk} - \bar{r}_j)}{\sqrt{\sum_{k=1}^{n}(r_{ik} - \bar{r}_i)^2}\sqrt{\sum_{k=1}^{n}(r_{jk} - \bar{r}_j)^2}}, \tag{18}$$

$$\sigma_i = \sqrt{\frac{1}{n}\sum_{k=1}^{n}(r_{ik} - \bar{r}_i)^2},\ \sigma_j = \sqrt{\frac{1}{n}\sum_{k=1}^{n}(r_{jk} - \bar{r}_j)^2}, \tag{19}$$

$$\zeta_{ij} = \frac{2\rho_{ij}\sigma_i\sigma_j}{\sigma_i^2 + \sigma_j^2 + (\bar{r}_i - \bar{r}_j)}, \tag{20}$$

where $\zeta_{ij} \in [-1, 1]$, ρ_{ij} is the pearson correlation coefficient of G_i and G_j, r_{ik} and r_{jk} are the normalized value of the evaluation indicator C_k for the supplier G_i and the supplier G_j, $\bar{r}_i$ and $\bar{r}_j$ are the average values of the normalized each indicator for the supplier G_i and the supplier G_j, respectively.

Let $G = \{G_1, \cdots, G_i, \cdots, G_m\}$ be a set of suppliers, let $C = \{C_1, \cdots, C_k, \cdots, C_n\}$ be a set of evaluation indicators, and let $N = \{N_1, \cdots, N_l, \cdots, N_z\}$ be a supplier portfolio. The concordance correlation coefficient ζ_{iN} between the supplier G_i and the supplier portfolio N is given by:

$$\zeta_{iN} = \max\{\zeta_{il}\}, l = 1, \cdots, l, \cdots, z, \tag{21}$$

Example 2. Let $G = \{G_1, \cdots, G_i, \cdots, G_m\}$ be a set of suppliers, let $C = \{C_1, C_2, C_3, C_4\}$ be a set of evaluation indicators, and let $N = \{N_1, N_2\}$ be a supplier portfolio that has been selected. Suppose the normalized values of evaluation indicators for the suppliers are shown in Table 2. Hence, the concordance correlation coefficient ζ_{GN} between the supplier G_i and the supplier portfolio N is calculated by Equation (21).

$$\zeta_{GN_1} = \frac{2\rho_{GN_1}\sigma_G\sigma_{N_1}}{\sigma_G^2 + \sigma_{N_1}^2 + (\bar{r}_G - \bar{r}_{N_1})} = 0.8334, \tag{22}$$

$$\zeta_{GN_2} = \frac{2\rho_{GN_2}\sigma_G\sigma_{N_2}}{\sigma_G^2 + \sigma_{N_2}^2 + (\bar{r}_G - \bar{r}_{N_2})} = 0.2778, \tag{23}$$

Therefore,

$$\zeta_{GN} = \max\left\{\zeta_{GN_1}, \zeta_{GN_2}\right\} = \zeta_{GN_1} = 0.8334. \tag{24}$$

2) THE SIMILARITY DEGREE OF SUPPLIERS

Let $G = \{G_1, \cdots, G_i, \cdots, G_m\}$ be a set of suppliers, let $C = \{C_1, \cdots, C_k, \cdots, C_n\}$ be a set of evaluation indicators, and let $N = \{N_1, \cdots, N_l, \cdots, N_z\}$ be a supplier portfolio. The similarity ψ_{ij} between the supplier G_i and the supplier G_j is given as follows:

$$\psi_{ij} = \begin{cases} 0 & -1 < \zeta_{ij} < 0 \\ (1-\mu_i)\zeta_{ij} & 0 \le \zeta_{ij} < 1 \end{cases}, \quad (25)$$

where μ_i is the membership degree of supplier G_i obtained by TOPSIS, which represents the indicator capability of the supplier G_i. The ζ_{ij} represents the concordance correlation coefficient between the supplier G_i and the supplier G_j, and $0 \le \psi_{ij} \le 1$. Then, the similarity ψ_{iN} between the supplier G_i and the supplier portfolio N is given as follows:

$$\psi_{iN} = \begin{cases} 0 & -1 < \zeta_{iN} < 0 \\ (1-\mu_i)\zeta_{iN} & 0 \le \zeta_{iN} < 1 \end{cases}, \quad (26)$$

where ζ_{iN} represents the concordance correlation coefficient between the supplier G_i and the supplier portfolio N, and $0 \le \psi_{iN} \le 1$.

The similarity of the supplier G_i with the supplier G_j (the supplier portfolio N) is denoted by the nonmembership degree of IFS: $\nu_i = \psi_{ij}$, $(\nu_i = \psi_{iN})$.

C. THE TOPSIS-NS METHOD FOR SUPPLIER PORTFOLIO SELECTION

When selecting a supplier portfolio, in order to improve the complementary capability of the supplier portfolio, the negative similarity among suppliers of the optimal portfolio should be reduced. The score function of IFS is proposed to select a supplier portfolio $N = \{N_1, \cdots, N_l, \cdots, N_z\}$ from a set of suppliers $G = \{G_1, \cdots, G_i, \cdots, G_m\}$, as follows:

Step 1: Initialize the set of suppliers $G = \{G_1, \cdots, G_i, \cdots, G_m\}$ and the supplier portfolio $N = \phi$.

Step 2: Calculate the indicator capability C_i of each supplier by Equation (16), which is denoted by the membership degree of IFS: $\mu_i = C_i$.

Step 3: Select the supplier G_i with the maximum C_i as the supplier N_d for the supplier portfolio N. Then, let the number of iterations $d = 1$.

Step 4: Update the set of suppliers $G = G \backslash \{N_d\}$ and the supplier portfolio $N = N \bigcup \{N_d\}$.

Step 5: Calculate the concordance correlation coefficient ζ_{iN} between the suppliers G_i and the supplier portfolio N by Equation (21).

Step 6: Calculate the similarity degree ψ_{iN} of suppliers G_i with supplier portfolio N by Equation (26), which is denoted by the nonmembership degree of IFS: $\nu_i = \psi_{iN}$.

Step 7: Calculate the comprehensive score $s(G_i)$ of the supplier G_i based on the following score function of IFS:

$$s_i = \mu_i - \nu_i, \quad (27)$$

where $\mu_i = C_i$, $\nu_i = \psi_{iN}$. So that $0 \le \mu_i + \nu_i \le 1$.

Step 8: Select the supplier G_i with the maximum $s(G_i)$ as suppliers N_d of the supplier portfolio. If the maximum $s(G_i)$ are the same, select a supplier with large competitive capability C_i as N_d.

Step 9: Let the number of iterations $d = d + 1$.

Step 10: If $d < z$, return to *Step 4*. If $d = z$, update the set of suppliers $G = G \backslash \{N_z\}$ and the supplier portfolio $N = N \bigcup \{N_z\}$. As a result, the end of this iteration.

Furthermore, the process of TOPSIS-NS for supplier portfolio selection is given in Figure 1.

D. THE TOPSIS-PS METHOD FOR SUPPLIER SUBSTITUTE SELECTION

When selecting a supplier substitute, to ensure that the selected substitute not only has high competitive capability but also has higher similarity with the best supplier. The accuracy function of IFS is proposed to select a supplier substitute G_i from a set of suppliers $G = G \backslash \{G_{best}\}$, as follows:

Step 1: Initialize the set of suppliers $G = \{G_1, \cdots, G_i, \cdots, G_m\}$ and the set of evaluation indicators $C = \{C_1, \cdots, C_k, \cdots, C_n\}$.

Step 2: According to TOPSIS, calculate the supplier's closeness coefficient and get the supplier's ranking, the first-ranked supplier is the best supplier G_{best}. From remaining suppliers, find one that is highly indicator capability and similarity to supplier G_{best} as a substitute for the supplier G_{best}.

Step 3: Calculate the indicator capability C_i of remaining suppliers by Equation (16), and denoted by the membership degree of IFS: $\mu_i = C_i$.

Step 4: Compare the indicator capabilities of remaining suppliers. Then, remove the bottom one-third of suppliers in descending order, ensure the set of substitutes has the higher indicator capability.

Step 5: Calculate the the concordance correlation coefficient ζ_{i-best} between the set of remaining suppliers G_i with the best supplier G_{best} by Equation (20).

Step 6: Calculate the similarity degree ψ_{i-best} between the set of remaining suppliers G_i with the best supplier G_{best} by Equation (25), and denoted by the nonmembership degree of IFS: $\nu_i = \psi_{i-best}$.

Step 7: Calculate the comprehensive score $h(G_i)$ of the supplier G_i based on the following accuracy function of IF:

$$h_i = \mu_i + \nu_i, \quad (28)$$

where $\mu_i = C_i$, $\nu_i = \psi_{i-best}$. So that $0 \le \mu_i + \nu_i \le 1$.

Step 8: Compare the comprehensive score $h(G_i)$, select the maximum scoring supplier G_i as a substitute for the best supplier G_{best}.

Furthermore, the process of the TOPSIS-PS for supplier substitute selection is given in Figure 2.

IV. ILLUSTRATIVE EXAMPLES

Example 1 for supplier portfolio selection and Example 2 for supplier substitute selection are given. In addition, the feasibility and superiority of TOPSIS-NS in supplier portfolio selection and TOPSIS-PS in supplier substitute selection is proved.

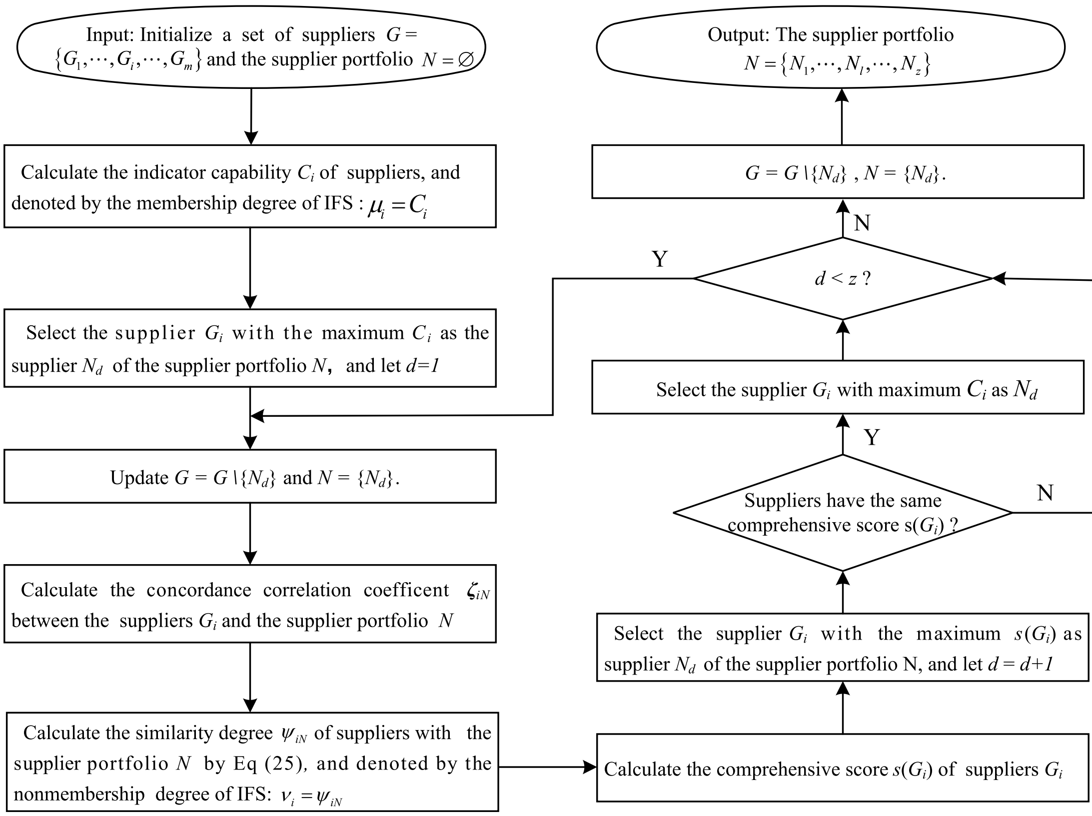


FIGURE 1. **The process of the TOPSIS-NS for supplier portfolio selection.**

A. EXAMPLE 1: SUPPLIER PORTFOLIO SELECTION

Example 1 [31] is to select eight potential suppliers from a set of interested suppliers $\{G_1, G_2, G_3, G_4, G_5, G_6, G_7, G_8, G_9, G_{10}, G_{11}, G_{12}\}$. In this case, the supplier pre-selection criteria $\{C_1, C_2, C_3, C_4, C_5, C_6, C_7, C_8\}$ and the relative weight ω are shown in Table 3. The normalized decision matrix of suppliers on these criteria are shown in Table 4. Then, the process for selecting eight suppliers using the TOPSIS-NS method is presented as follows:

Step 1: Initialize the set of suppliers $\{G_1,G_2,G_3,G_4,G_6,G_7,G_8,G_9,G_{10},G_{12}\}$ and the supplier portfolio $N = \phi$.

Step 2: Calculate the membership degree μ_i of each supplier G_i by Equation (16), $\mu = (0.4182, 0.3916, 0.6355, 0.3731, 0.4248, 0.4711, 0.5871, 0.1577, 0.5945, 0.1577, 0.8119, 0.7742)$, which is shown in table 5.

Step 3: Select the suppliers G_{11} with the maximum μ_{11} as the first supplier N_1 for the supplier portfolio. Then, let the number of iterations $d = 1$.

Step 4: Update the set of suppliers $G = G \setminus \{N_d\} = \{G_1,G_2,G_3,G_4,G_6,G_7,G_8,G_9,G_{10},G_{12}\}$ and the supplier portfolio $N = N \bigcup \{N_d\} = G_{11}$.

Step 5: Calculate the concordance correlation coefficient ζ_{iN} between the set of suppliers G and the supplier portfolio N by Equation (21). which is shown in Table 5.

Step 6: Calculate the nonmembership degree ν_i of suppliers G_i by Equation (26), which is shown in Table 5.

Step 7: Calculate the comprehensive score $s(G_i)$ of suppliers $G = G \setminus \{N_d\}$ by Equation (27), which is shown in Table 5.

Step 8: From Table 5, it can be seen that $s(G_{12})$ with the maximum comprehensive score was selected as the second supplier N_2 of supplier portfolios.

Step 9: Let the number of iterations $d = d + 1$.

And so on, $(N_3 = G_3, N_4 = G_9, N_5 = G_7, N_6 = G_4, N_7 = G_2, N_8 = G_6)$. Hence, the supplier portfolio selected through TOPSIS-NS is $N = \{G_{11},G_{12},G_3,G_9,G_7,G_4,G_2,G_6\}$.

B. EXAMPLE 2: SUPPLIER SUBSTITUTE SELECTION

Example 2 [32] is to select the best supplier of Quarry Natural Aggregate among suppliers $\{G_1, G_2, G_3, G_4, G_5, G_6, G_7\}$ associated with criteria $\{C_1, C_2, C_3, C_4, C_5, C_6, C_7\}$. In this case, the criteria names and weights are shown in Table 6. The result of normalization of the suppliers' performances' values is presented in Table 7. Then, the process for selecting a substitute for the best supplier by the TOPSIS-PS method is presented as follows:

Step 1: Initialize the set of suppliers $\{G_1,G_2,G_3,G_4,G_5,G_6,G_7\}$ and their evaluation criteria $\{C_1, C_2, C_3, C_4, C_5, C_6, C_7\}$.

Step 2: G_4 ranks first by the TOPSIS method, so which selects the best supplier is G_4.

Step 3: Calculate the membership degree of remaining suppliers by Equation (16), $(G_1 = 0.3945, G_2 = 0.3657,$

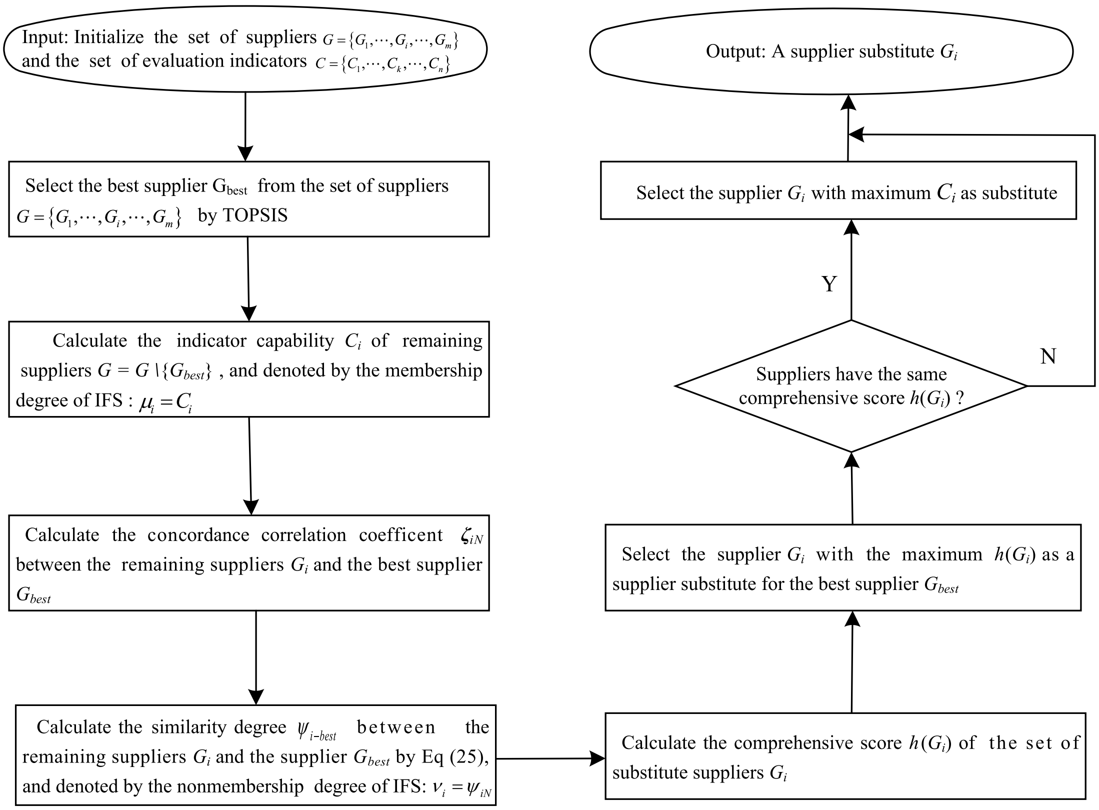


FIGURE 2. The process of TOPSIS-PS for supplier substitute selection.

TABLE 3. Selection criteria and sub-criteria of supplier.

Criteria	Sub-Criteria	Notation	Weight	
			ω	Values
General characteristic	Production facilities and capacity	C_1	ω_1	0.100
	Technical capability	C_2	ω_2	0.100
	Financial position	C_3	ω_3	0.100
	Management and organisation	C_4	ω_4	0.100
	Environmental performance	C_5	ω_5	0.100
History performance	Quality performance history	C_6	ω_6	0.167
	Delivery performance history	C_7	ω_7	0.167
	Service performance history	C_8	ω_8	0.167

$G_3 = 0.3957$, $G_5 = 0.3914$, $G_6 = 0.4935$, $G_7 = 0.4270$) is displayed in Table 8.

Step 4: Compare the membership degree of the remaining suppliers. Remove the bottom third of the list of remaining suppliers in descending order, hence, this the set of substitutes is $\{G_1, G_3, G_6, G_7\}$.

Step 5: Calculate the concordance correlation coefficient ζ_{i-4} between the set of remaining suppliers G with the best supplier G_4, which is shown in Table 8.

Step 6: Calculate the nonmembership degree ν_i of remaining suppliers G_i, which is shown in Table 8.

Step 7: Calculate the comprehensive score $h(G_i)$ of the suppliers $G = \{G_1, G_3, G_6, G_7\}$ by Equation (28), which is shown in Table 8.

Step 8: From Table 8, it can be seen that $h(G_7)$ with the maximum comprehensive score was selected as the substitute for supplier G_4.

V. COMPARATIVE ANALYSIS

To demonstrate the advantages of the TOPSIS-NS in selecting supplier portfolios and the TOPSIS-PS in selecting supplier substitutes, two comparative analyses are conducted based on Example 1 for supplier portfolios selection and Example 2 for supplier substitutes selection.

A. COMPARISON OF SUPPLIER PORTFOLIO SELECTION METHODS

In order to illustrate the superiority of the TOPSIS-NS method for supplier portfolios selection over other methods, the traditional TOPSIS method proposed by [17], the modified TOPSIS method (Abootalebi et al.'s method) proposed by [18] and the PROMETHEE V method proposed by [16] are applied to calculate the illustrative example obtained from [31], and the results of these methods are shown in Table 9.

TABLE 4. Normalized decision matrix.

Suppliers G_i	Evaluation indicators C_j: C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
G_1	0.750	0.500	0.750	0.500	0.750	0.500	0.750	0.500
G_2	0.750	0.500	0.958	0.750	0.500	0.750	0.500	0.500
G_3	0.500	0.750	0.958	0.500	0.750	0.750	0.958	0.750
G_4	0.750	0.958	0.750	0.500	0.750	0.500	0.250	0.750
G_5	0.750	0.250	0.500	0.750	0.500	0.500	0.750	0.750
G_6	0.750	0.750	0.500	0.750	0.750	0.750	0.500	0.750
G_7	0.500	0.500	0.750	0.500	0.750	0.750	0.958	0.750
G_8	0.500	0.250	0.750	0.500	0.750	0.500	0.250	0.500
G_9	0.750	0.500	0.500	0.750	0.750	0.958	0.750	0.750
G_{10}	0.750	0.250	0.750	0.500	0.500	0.500	0.250	0.500
G_{11}	0.958	0.958	0.750	0.958	0.958	0.958	0.750	0.958
G_{12}	0.750	0.750	0.958	0.958	0.750	0.958	0.958	0.750

TABLE 5. The membership degree μ_i, the concordance correlation coefficient ζ_{iN}, the nonmembership degree ν_{iN}, the comprehensive score $s(G_i)$ and the ranking of suppliers.

	Suppliers G_i: G_1	G_2	G_3	G_4	G_5	G_6	G_7	G_8	G_9	G_{10}	G_{11}	G_{12}
μ_i	0.4182	0.3916	0.6355	0.3731	0.4248	0.4711	0.5871	0.1577	0.5945	0.1577	**0.8119**	0.7742
$\zeta_{iN}(d=2)$	0.3666	0.4646	0.6318	0.3678	0.6455	0.9019	0.6905	0.3133	0.8851	0.3133	-	0.7574
$\zeta_{iN}(d=3)$	0.6159	0.6441	0.8662	0.3678	0.7015	0.9019	0.8880	0.3133	0.8851	0.3133	-	-
$\zeta_{iN}(d=4)$	0.7175	0.6441	-	0.3678	0.7015	0.9019	0.9647	0.3133	0.8851	0.3133	-	-
$\zeta_{iN}(d=5)$	0.7175	0.6441	-	0.3678	0.7380	0.9019	0.9647	0.3437	-	0.3437	-	-
$\zeta_{iN}(d=6)$	0.7375	0.6441	-	0.3678	0.7714	0.9019	-	0.3437	-	0.3437	-	-
$\zeta_{iN}(d=7)$	0.7375	0.6441	-	-	0.7714	0.9019	-	0.3587	-	0.3587	-	-
$\zeta_{iN}(d=8)$	0.7375	0.7714	-	-	-	0.9019	-	0.5102	-	0.6712	-	-
$\nu_i(d=2)$	0.2133	0.2827	0.2303	0.2306	0.3713	0.4770	0.2851	0.2639	0.3589	0.2639	-	0.1710
$\nu_i(d=3)$	0.3583	0.3919	0.3158	0.2306	0.4035	0.4770	0.3667	0.2639	0.3589	0.2639	-	-
$\nu_i(d=4)$	0.4174	0.3919	-	0.2306	0.4035	0.4770	0.3983	0.2639	0.3589	0.2639	-	-
$\nu_i(d=5)$	0.4174	0.3919	-	0.2306	0.4245	0.4770	0.3983	0.2895	-	0.2895	-	-
$\nu_i(d=6)$	0.4291	0.3919	-	0.2306	0.4437	0.4770	-	0.2895	-	0.2895	-	-
$\nu_i(d=7)$	0.4291	0.3919	-	-	0.4437	0.4770	-	0.3021	-	0.3021	-	-
$\nu_i(d=8)$	0.4291	-	-	-	0.4437	0.4770	-	0.4297	-	0.5654	-	-
$s(G_i)(d=2)$	0.2049	0.1089	0.4052	0.1426	0.0536	-0.0059	0.3020	-0.1062	0.2356	-0.1062	-	**0.6032**
$s(G_i)(d=3)$	0.0599	-0.0003	**0.3197**	0.1426	0.0213	-0.0059	0.2204	-0.1062	0.2356	-0.1062	-	-
$s(G_i)(d=4)$	0.0008	-0.0003	-	0.1426	0.0213	-0.0059	0.1888	-0.1062	**0.2356**	-0.1062	-	-
$s(G_i)(d=5)$	0.0008	-0.0003	-	0.1426	0.0004	-0.0059	**0.1888**	-0.1319	-	-0.1319	-	-
$s(G_i)(d=6)$	-0.0109	-0.0003	-	**0.1426**	-0.0189	-0.0059	-	-0.1318	-	-0.1318	-	-
$s(G_i)(d=7)$	-0.0109	**-0.0003**	-	-	-0.0189	-0.0059	-	-0.1445	-	-0.1445	-	-
$s(G_i)(d=8)$	-0.0109	-	-	-	-0.0189	**-0.0059**	-	-0.2721	-	-0.4077	-	-
Ranking(d=2)	5	7	2	6	8	9	3	10	4	11	-	**1**
Ranking(d=3)	5	7	**1**	4	6	8	3	9	2	10	-	-
Ranking(d=4)	5	6	-	3	4	7	2	8	**1**	9	-	-
Ranking(d=5)	3	5	-	2	4	6	**1**	7	-	8	-	-
Ranking(d=6)	4	2	-	**1**	5	3	-	6	-	7	-	-
Ranking(d=7)	3	**1**	-	-	4	2	-	5	-	6	-	-
Ranking(d=8)	2	-	-	-	3	**1**	-	4	-	5	-	-

TABLE 6. Result of the criteria weights.

Criteria C_j	Definition of criteria	Weight: ω	Values
C_1	Acquisition price per ton	ω_1	0.3856
C_2	Transport price per ton per kilometer	ω_2	0.1928
C_3	Transport distance	ω_3	0.1286
C_4	Quality of QNA	ω_4	0.0964
C_5	Delivery time	ω_5	0.0772
C_6	Guarantee policy	ω_6	0.0643
C_7	Rejection level	ω_7	0.0551

Table 9 shows the results of selecting supplier portfolios of the traditional TOPSIS method, the PROMETHEE V method, the Abootalebi et al.'s method and the proposed TOPSIS-NS method. It can be seen that the supplier portfolio

TABLE 7. Normalized decision matrix.

Suppliers G_i	Selection criteria C_j C_1	C_2	C_3	C_4	C_5	C_6	C_7
G_1	0.3756	0.3490	0.5109	0.4472	0.1178	0.3000	0.5669
G_2	0.3615	0.3908	0.4905	0.2981	0.4714	0.4000	0.1889
G_3	0.3568	0.3769	0.3065	0.4472	0.4714	0.3000	0.3779
G_4	0.3850	0.3350	0.2043	0.1490	0.2357	0.5000	0
G_5	0.3991	0.4188	0.2452	0.4472	0.5892	0.4000	0.3779
G_6	0.3944	0.4048	0.3678	0.2981	0.1178	0.3000	0.5669
G_7	0.3709	0.3629	0.4087	0.4472	0.3535	0.4000	0.1889

TABLE 8. The membership degree μ_i, the concordance correlation coefficient ζ_{i-best}, the nonmembership degree ν_i, the comprehensive score $h(G_i)$, and the ranking of suppliers.

	Suppliers G_i G_1	G_2	G_3	G_4	G_5	G_6	G_7
$C = \mu_i$	0.3945	0.3657	0.3957	0.8663	0.3914	0.4935	0.4270
ζ_{i-best}	0.8954	-	0.9379	1	-	0.9466	0.9541
$\psi_i = \nu_i$	0.5950	-	0.5661	-	-	0.5350	0.5771
$h(G_i)$	0.9305	-	0.9625	-	-	0.9698	**0.9723**
Ranking	4	-	3	-	-	2	**1**

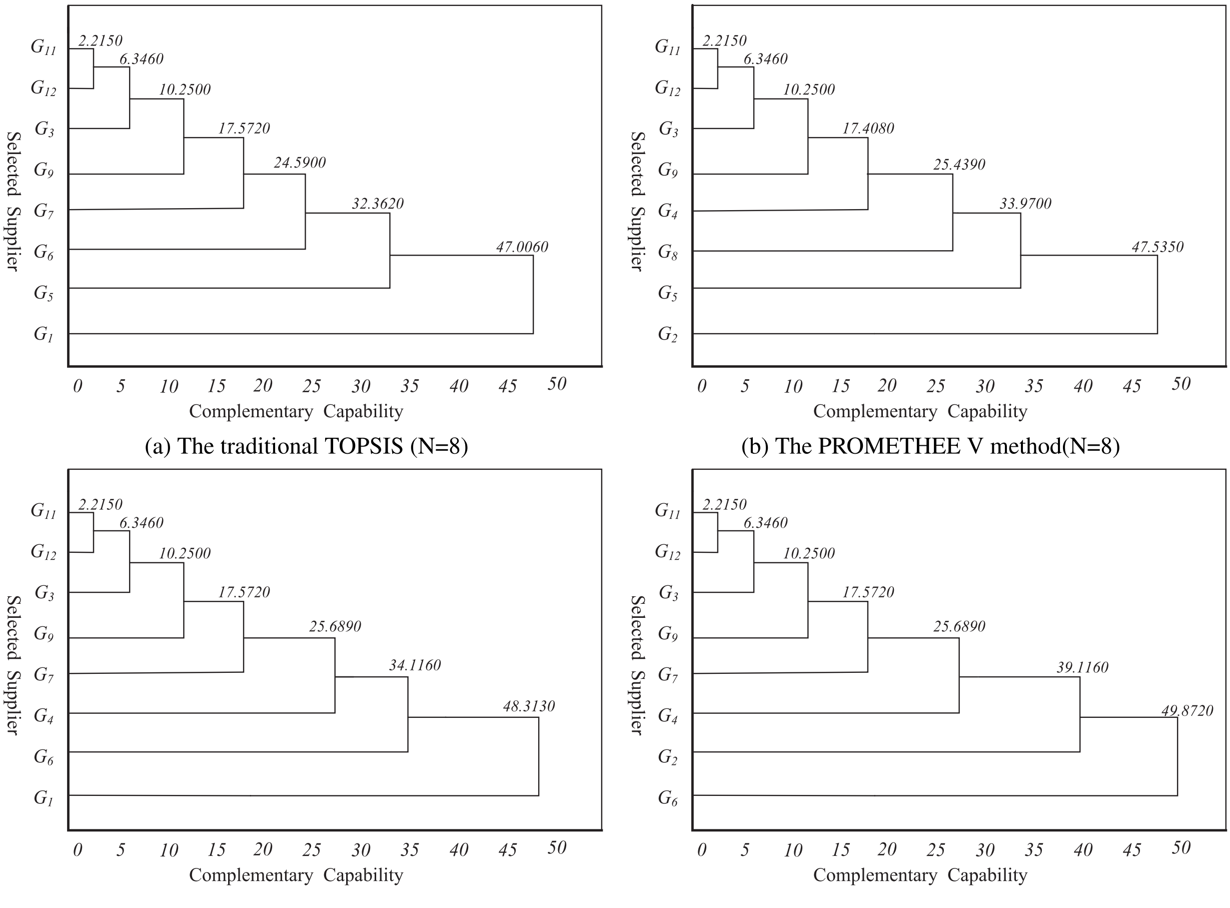


FIGURE 3. Comparison of supplier selection processes obtained by the traditional TOPSIS, the PROMETHEE V, the modified TOPSIS and the proposed TOPSIS-PS.

selection results of the three methods are different. Considering the complementary capabilities within the optimal portfolio, the TOPSIS-NS method can obtain the most ideal supplier portfolio. The complementary capabilities *CC* of the supplier portfolio selected by TOPSIS-NS is higher than those selected by the TOPSIS method, the PROMETHEE

TABLE 9. The optimal supplier portfolio based on the new proposed approach TOPSIS-NS and their comparison with the previous approaches.

Approaches	selection results	CC
The traditional TOPSIS [17]	$\{G_1, G_3, G_5, G_6, G_7, G_9, G_{11}, G_{12}\}$	47.0060
The PROMETHEE V method [16]	$\{G_1, G_4, G_6, G_8, G_7, G_9, G_{11}, G_{12}\}$	47.5350
The Abootalebi et al.'s method [18]	$\{G_1, G_3, G_4, G_6, G_7, G_9, G_{11}, G_{12}\}$	48.3130
The proposed TOPSIS-NS	$\{G_2, G_3, G_4, G_6, G_7, G_9, G_{11}, G_{12}\}$	49.8720

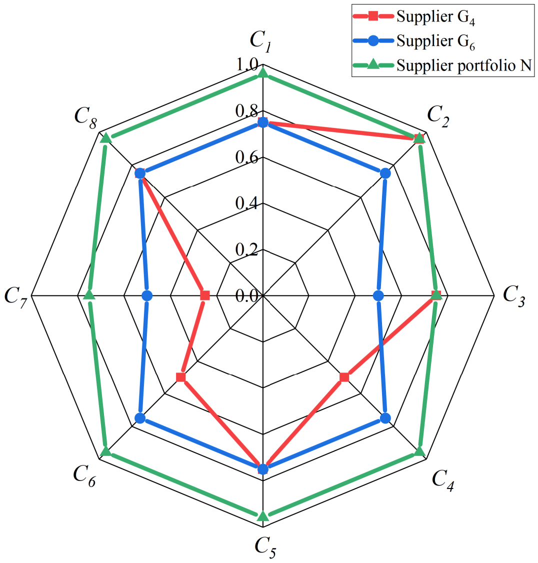


FIGURE 4. Comparison of the sixth supplier selection for methods TOPSIS and TOPSIS-NS.

V method, and the S. Abootalebi et al.'s method. It can be demonstrated that the TOPSIS-NS method can select the optimal supplier portfolio.

In addition, Figure 3 shows the supplier selection process of the TOPSIS method, the PROMETHEE V method, the Abootalebi et al.'s method and the proposed TOPSIS-NS method respectively, with CC representing the complementary capabilities of the selected supplier portfolios. The first four suppliers selected by the TOPSIS method, the PROMETHEE V method, and the TOPSIS-NS method were the same, and they all selected the better suppliers into the portfolio, which showed the feasibility of TOPSIS-NS in the supplier portfolio selection. But with the increase of the number of suppliers in the portfolio, the supplier portfolio selected by the TOPSIS method, the PROMETHEE V method, the Abootalebi et al.'s method and the proposed TOPSIS-NS method has different results, and the supplier portfolio selected by the TOPSIS-NS method has higher complementary capability. It can be shown that TOPSIS-NS can effectively reduce the negative influence of similarity in the supplier portfolio and that TOPSIS-NS has superiority in supplier portfolio selection.

Furthermore, to explain the differences select supplier into the portfolio among the three methods, we cite the example of TOPSIS and TOPSIS-NS selecting the sixth supplier. Figure 4 shows the similarity between the sixth selected supplier and the supplier portfolio ($N = \{G_{11}, G_{12}, G_3, G_9, G_7\}$) for TOPSIS and TOPSIS-NS. The sixth supplier selected by TOPSIS is G_6, while the sixth supplier selected by TOPSIS-NS is G_4. According to the Equation (21), $\zeta_{G_4-N} = \max\left\{\zeta_{G_4-l}\right\} = \zeta_{G_4-G_{11}}$ and $\zeta_{G_6-N} = \max\left\{\zeta_{G_6-l}\right\} = \zeta_{G_6-G_{11}}$, so selecting the evaluation indicators of G_{11} as the evaluation indicators of the supplier portfolio N. From Figure 4, it can be seen that G_4 has lower similarity with the supplier portfolio N, so G_4 was selected as the sixth supplier member of the supplier portfolio. This can indicate that the supplier portfolio selected through TOPSIS-NS can reduce the negative influence of similarity and integrate competitive capabilities among suppliers.

It is not surprising that the TOPSIS-NS method brings the best values. Furthermore, it is worth noticing that the TOPSIS-NS method performs more better in comparison with the other methods for supplier portfolio selection. (Note that the comparison of selection results and complementary capabilities in Table 9 can intuitively evaluated for these methods.)

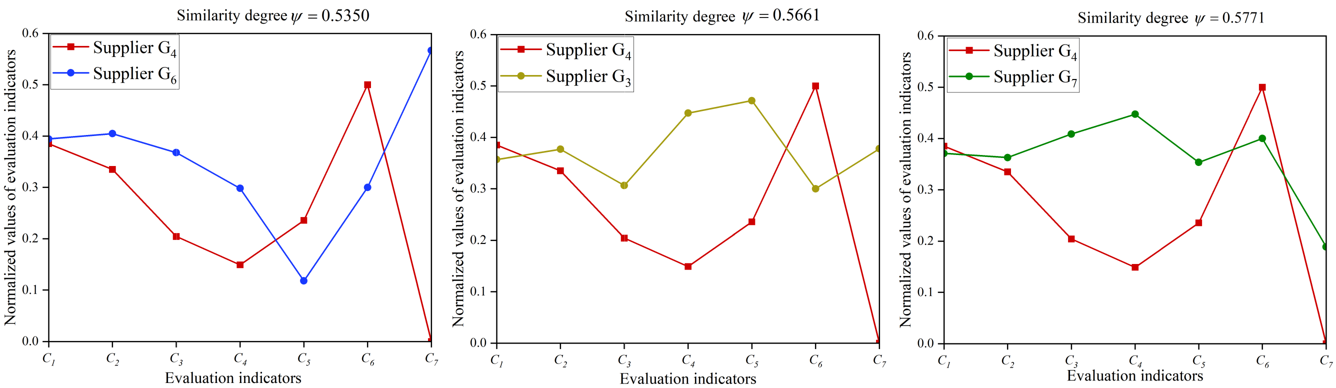
B. COMPARISON OF SUPPLIER SUBSTITUTE SELECTION METHODS

In order to illustrate the effectiveness and the superiority of the TOPSIS-PS method for supplier substitute selection over other methods, the traditional TOPSIS method proposed by [17], the modified TOPSIS method (Abootalebi et al.'s method) [18] and the VIKOR method proposed by [13] are applied to calculate the illustrative example obtained from [32]. In Example [32], the results obtained from the traditional TOPSIS, the Aootalebi et al.'s method, VIKOR and the proposed TOPSIS-PS, those method is all about selecting supplier G_4 as the best supplier for the company. Based on these four methods, select the most suitable substitute for the best supplier G_4, and the results of these methods are shown in Table 10.

Table 10 shows the results of the substitute selection of the best suppliers and the similarity to the best supplier G_4. It can be seen that the substitute selection results of TOPSIS-PS are different from TOPSIS, VIKOR and the Abootalebi et al.'s method, furthermore, the substitute selection results G_7 through TOPSIS-PS have a higher similarity with the best supplier. In addition, G_7 has a higher comprehensive score compared to G_6 and G_3, indicating that G_7 not only has high indicator capability but also high similarity with the best supplier, i.e., G_7 is more suitable as a substitute for G_4.

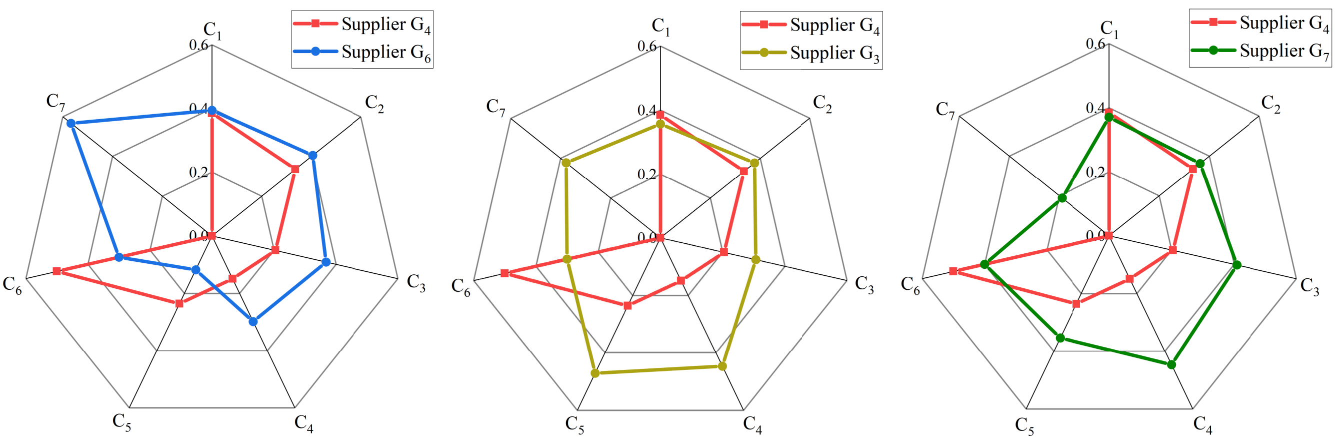
TABLE 10. **The optimal supplier substitute based on the new proposed approach TOPSIS-PS and their comparison with the previous approaches.**

Approaches	selection results	ν_i	$h(G_i)$
The traditional TOPSIS [17]	G_6	0.5350	0.9698
The VIKOR method [13]	G_3	0.5661	0.9625
The Abootalebi et al.'s method [18]	G_6	0.5350	0.9698
The proposed TOPSIS-PS	G_7	0.5771	0.9723



(a) TOPSIS and the [19]'s method (b) The VIKOR method (c) The proposed TOPSIS-PS

FIGURE 5. **Comparison of evaluation indicators of the substitute selected by the TOPSIS, the Abootalebi et al.'s method, the VIKOR, and the proposed TOPSIS-PS.**



(a) TOPSIS and the [19]'s method (b) The VIKOR method (c) The proposed TOPSIS-PS

FIGURE 6. **Comparison of similarity of the substitute selected by the TOPSIS, the Abootalebi et al.'s method, the VIKOR, and the proposed TOPSIS-PS with the best supplier G_4.**

This indicates the feasibility of TOPSIS-PS in the supplier portfolio selection, and TOPSIS-PS can obtain a more ideal supplier substitute.

Figure 5 shows the comparison of evaluation indicator values of supplier substitute selected by the TOPSIS method, the VIKOR method, S. Abootalebi et al.'s method and TOPSIS-PS, where C_6 is the benefit indicator and $\{C_1, C_2, C_3, C_4, C_5, C_7\}$ is the cost indicators. As can be seen from Figure 6, the substitute supplier G_7 selected by TOPSIS-PS has the highest similarity with the best supplier. In addition, through the accuracy function $h = \mu + \nu$, not only can the competitive capability (membership degree) of substitute suppliers be ensured, but also substitutes with a high similarity (nonmembership degree) to the best supplier can be selected. The results indicate that TOPSIS-PS has higher superiority in supplier substitute selection.

These features demonstrate that TOPSIS PS has stronger discriminative power, higher effectiveness, and superiority compared to previous methods. (Note that the comparison of selection results and similarity with the best supplier in Table 10 can intuitively evaluated for these methods.)

VI. CONCLUSION

In this paper, we analyzed the limitations of MCDM method in the optimal selections of supplier portfolio and supplier substitute that ignores the bidirectional influence of similarity (positive similarity or negative similarity) among suppliers, and two methods (TOPSIS-NS and TOPSIS-PS) are proposed for the optimal selections of supplier portfolio and supplier substitute, respectively. In proposed TOPSIS-NS and TOPSIS-PS methods, suppliers are selected comprehensively from two aspects: the membership degree μ of IFS and the nonmembership degree ν of IFS aspects. The membership degree μ of IFS is the indicator capability of suppliers, while the nonmembership degree ν of IFS is the bidirectional similarity among suppliers. When selecting a supplier portfolio, the supplier portfolio considering the negative influence of similarity is comprehensively selected by the score function of IFS. When selecting a supplier substitute, the supplier substitute considering the postive influence of similarity is comprehensively selected by the accuracy function of IFS.

By comparing two examples from reference [31], [32], we can find the feasibility and the superiority of TOPSIS-NS in supplier portfolio selection [31] and TOPSIS-PS in supplier substitute selection [32] respectively. The superiority of TOPSIS-NS in supplier portfolio selection: (1) The TOPSIS-NS not only considers the competitive capabilities of each supplier, but also considers the negative infulence of similarity among suppliers. (2) The TOPSIS-NS can reduce the similarity of the selected supplier portfolio (Refer to Table 8), and enhance the complementary capability (CC) of the supplier portfolio (Refer to Table 9). (3) The TOPSIS-NS integrates the different competitive capabilities of each supplier, supplementing the limitations of TOPSIS in selecting supplier portfolios. The superiority of TOPSIS-PS in supplier substitute selection: (1) The TOPSIS-PS not only considers the competitive capability of the supplier substitute, but also considers the positive infulence of similarity between the substitute with the best supplier. (2) The similarity between the substitute selected by TOPSIS-PS and the best supplier is higher than that between the substitute selected by orther methods and the best supplier (Refer to Table 10).

In conclusion, the TOPSIS-NS is superior to other methods in supplier portfolio selection and the TOPSIS-PS to other methods in supplier substitute selection if similarity is considered. This paper comprehensively considers the indicator capabilities of suppliers and the bidirectional influence of similarity among suppliers, which helps to select suitable suppliers as portfolio members or substitutes for the best supplier, and make up the shortcomings of MCDM method in supplier selection. In addition, due to the wide application of MCDM method, considering the future, we will extend our proposed viewpoint of considering the similarity among alternatives to fuzzy MCDM methods. And pay more attention to the measure of similarty for these methods.

REFERENCES

[1] D. Kannan, "Role of multiple stakeholders and the critical success factor theory for the sustainable supplier selection process," *Int. J. Prod. Econ.*, vol. 195, pp. 391–418, Jan. 2018.
[2] C. Neumüller, R. Lasch, and F. Kellner, "Integrating sustainability into strategic supplier portfolio selection," *Manage. Decis.*, vol. 54, no. 1, pp. 194–221, Feb. 2016.
[3] M. H. Dani, "Study of supplier selection process under strategic outsourcing conditions," Doctoral dissertation, Dept. Manag. Stud., Goa Univ., Taleigao, Goa, 2017.
[4] C.-J. Lin and P.-Y. Lin, "A step-up approach for selecting substitute suppliers under nonlinear profile data," *Qual. Technol. Quant. Manage.*, vol. 18, no. 5, pp. 641–655, Jul. 2021.
[5] A. Ayough, S. B. Shargh, and B. Khorshidvand, "A new integrated approach based on base-criterion and utility additive methods and its application to supplier selection problem," *Expert Syst. Appl.*, vol. 221, Jul. 2023, Art. no. 119740.
[6] S. Gupta, P. Chatterjee, M. Yazdani, and E. D. R. S. Gonzalez, "A multi-level programming model for green supplier selection," *Manage. Decis.*, vol. 59, no. 10, pp. 2496–2527, Sep. 2021.
[7] A. S. K. Kannan, S. A. A. Balamurugan, and S. Sasikala, "A customized metaheuristic approaches for improving supplier selection in intelligent decision making," *IEEE Access*, vol. 9, pp. 56228–56239, 2021.
[8] L. Shi, K. Huang, Y. Liu, F. Ge, and S. Liu, "Risk assessment in supplier selection for intelligent manufacturing systems based on PLS-SEM," *Appl. Sci.*, vol. 12, no. 8, p. 3998, Apr. 2022.
[9] A. Majumdar, M. Kaliyan, and R. Agrawal, "Selection of resilient suppliers in manufacturing industries post-COVID-19: Implications for economic and social sustainability in emerging economies," *Int. J. Emerg. Markets*, vol. 18, no. 10, pp. 3657–3675, Nov. 2023.
[10] T. E. Saputro, G. Figueira, and B. Almada-Lobo, "Hybrid MCDM and simulation-optimization for strategic supplier selection," *Expert Syst. Appl.*, vol. 219, Jun. 2023, Art. no. 119624.
[11] A. Hosseininasab and A. Ahmadi, "Selecting a supplier portfolio with value, development, and risk consideration," *Eur. J. Oper. Res.*, vol. 245, no. 1, pp. 146–156, Aug. 2015.
[12] I. Tronnebati, M. El Yadari, and F. Jawab, "A review of green supplier evaluation and selection issues using MCDM, MP and AI models," *Sustainability*, vol. 14, no. 24, p. 16714, Dec. 2022.
[13] B. Rahardjo, F.-K. Wang, S.-C. Lo, and J.-H. Chou, "A hybrid multi-criteria decision-making model combining DANP with VIKOR for sustainable supplier selection in electronics industry," *Sustainability*, vol. 15, no. 5, p. 4588, Mar. 2023.
[14] C.-H. Chen, "A novel multi-criteria decision-making model for building material supplier selection based on entropy-AHP weighted TOPSIS," *Entropy*, vol. 22, no. 2, p. 259, Feb. 2020.
[15] J. P. Brans, B. Mareschal, and P. Vincke, "A new family of outranking methods in multi-criteria analysis," in *Cahiers du Centre d'études de Recherche Opérationnelle*. Brussels, Belgium: Universite Libre de Bruxelles, 1984, pp. 3–24.
[16] J. P. Brans and B. Mareschal, "PROMETHEE V: MCDM problems with segmentation constraints," *Inf. Syst. Oper. Res.*, vol. 30, no. 2, pp. 85–96, May 2016.
[17] C. L. Hwang and K. Yoon, "Methods for multiple attribute decision making," in *Multiple Attribute Decision Making*. Berlin, Germany: Springer, 1981, p. 58191.
[18] S. Abootalebi, A. Hadi-Vencheh, and A. Jamshidi, "Ranking the alternatives with a modified TOPSIS method in multiple attribute decision making problems," *IEEE Trans. Eng. Manag.*, vol. 69, no. 5, pp. 1800–1805, Oct. 2022.
[19] H.-W. Lo, J. J. H. Liou, H.-S. Wang, and Y.-S. Tsai, "An integrated model for solving problems in green supplier selection and order allocation," *J. Cleaner Prod.*, vol. 190, pp. 339–352, Jul. 2018.
[20] G. Selvachandran and X. Peng, "A modified TOPSIS method based on vague parameterized vague soft sets and its application to supplier selection problems," *Neural Comput. Appl.*, vol. 31, no. 10, pp. 5901–5916, Mar. 2018.
[21] Z. G. Arens and R. W. Hamilton, "The substitution strategy dilemma: Substitute selection versus substitute effectiveness," *J. Acad. Marketing Sci.*, vol. 46, no. 1, pp. 130–146, Jun. 2017.
[22] K. T. Atanassov, "Intuitionistic fuzzy sets," *Fuzzy Sets Syst.*, vol. 20, no. 1, pp. 87–96, Aug. 1986.
[23] C. V. Negoita, "Fuzzy sets," *Fuzzy Sets Syst.*, vol. 133, no. 2, p. 275, Jan. 2003.
[24] H. Garg and K. Kumar, "An advanced study on the similarity measures of intuitionistic fuzzy sets based on the set pair analysis theory and their application in decision making," *Soft Comput.*, vol. 22, no. 15, pp. 4959–4970, Apr. 2018.

[25] S. Jeevaraj, "Similarity measure on interval valued intuitionistic fuzzy numbers based on non-hesitance score and its application to pattern recognition," *Comput. Appl. Math.*, vol. 39, no. 3, p. 212, Jul. 2020.
[26] V. L. G. Nayagam, D. Ponnialagan, and S. Jeevaraj, "Similarity measure on incomplete imprecise interval information and its applications," *Neural Comput. Appl.*, vol. 32, no. 8, pp. 3749–3761, Apr. 2020.
[27] S.-M. Chen and J.-M. Tan, "Handling multicriteria fuzzy decision-making problems based on vague set theory," *Fuzzy Sets Syst.*, vol. 67, no. 2, pp. 163–172, Oct. 1994.
[28] D. H. Hong and C.-H. Choi, "Multicriteria fuzzy decision-making problems based on vague set theory," *Fuzzy Sets Syst.*, vol. 114, no. 1, pp. 103–113, Aug. 2000.
[29] C. Chen, S. Zhang, J. Chu, S. Yu, N. Ding, H. Zhao, Z. Su, and H. Fan, "Member combination selection for product collaborative design under the open innovation model," *Adv. Eng. Informat.*, vol. 55, Jan. 2023, Art. no. 101860.
[30] L. I.-K. Lin, "A concordance correlation coefficient to evaluate reproducibility," *Biometrics*, vol. 45, no. 1, p. 255, Mar. 1989.
[31] C. Yu and T. N. Wong, "A supplier pre-selection model for multiple products with synergy effect," *Int. J. Prod. Res.*, vol. 52, no. 17, pp. 5206–5222, Mar. 2014.
[32] S. Bouhedja, A. Boukhaled, A. Bouhedja, and A. Benselhoub, "Use of the TOPSIS technique to choose the best supplier of quarry natural aggregate," *Mining Mineral Deposits*, vol. 14, no. 1, pp. 11–18, Mar. 2020.

CHAO WANG received the B.Eng., M.Eng., and Ph.D. degrees in mathematics from Hebei University, Baoding, China, in 2006, 2009, and 2013, respectively. He is currently the Dean of the School of Information and Electrical Engineering, Hebei University of Engineering, and also the Director of the Chinese Society of Industrial and Applied Mathematics, a member of the Fuzzy Mathematics and Fuzzy Systems Professional Committee of the Chinese Society of Systems Engineering, and the Executive Director and the General Deputy Secretary of the Hebei Society of Industrial and Applied Mathematics. His research interests include machine learning and support vector machine and its application in management prediction and decision.

JIAXIN SHI received the B.Eng. degree from the Hebei University of Engineering, Handan, China, where he is currently pursuing the M.Eng. degree in management engineering and business. His research interests include uncertain decision making and machine learning.

YANG YANG received the B.Eng., M.Eng., and Ph.D. degrees in management science and engineering from Hebei University, Baoding, China, in 2009, 2012, and 2015, respectively. Currently, she is a Master Supervisor in management engineering and business with the Hebei University of Engineering. Her research interests include machine learning, uncertain networks and uncertain statistical prediction, and decision-making.

RUI WANG received the B.Eng. degree from the Hebei University of Engineering, Handan, China, where he is currently pursuing the M.Eng. degree in management engineering and business. His research interests include uncertain decision making and machine learning.