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Taxonomy Method for Multiple Attribute Group Decision Making Under the Spherical Fuzzy Environment

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Abstract. In recent years, the multi-attribute group decision making (MAGDM) problem has received extensive attention and research, and it plays an increasingly important role in our daily life. Fuzzy environment provides a more accurate decision-making environment for decision makers, so the research on MAGDM problem under fuzzy environment sets (SFSs) has become popular. Taxonomy method has become an effective method to solve the problem of MAGDM. It also plays an important role in solving the problem of MAGDM combined with other environments. In this paper, a new method for MAGDM is proposed by combining Taxonomy method with SFSs (SF-Taxonomy). In addition, we use entropy weight method to calculate the objective weight of attributes, so that more objective results can be produced when solving MAGDM problems.

Key words: multi-attribute group decision-making (MAGDM), spherical fuzzy sets (SFSs), taxonomy, entropy method.

1. Introduction

In order to improve the accuracy of decision-making, Zadeh (1965) put forward the concept of a fuzzy set, in which the relationship between hesitation degree, membership degree and non-membership degree is expounded. Many scholars have done related research on the fuzzy set and extended it further (Li and Wan, 2014a, 2014b; Lei *et al.*, 2021a, 2021b, Wei *et al.*, 2021). On the basis of predecessors, Atanassov (1986) proposed intuitionistic fuzzy sets (IFSs), so many scholars have studied the problem of MADM based on IFSs (Xian *et al.*, 2017a, 2017b; Ye, 2017; Garg, 2018a, 2018b). For example, Liu *et al.* (2021) used IFSs to deal with uncertainty in data. Kaur and Garg (2018) presented an intuitionistic method for cubic intuitionistic fuzzy environment and carried out a comparative analysis. Liu *et al.* (2021) proposed an improved precision function to accurately compare some interval IFSs. Xu *et al.* (2012) used IFSs to deal with the problem of information uncertainty in air target threat assessment. Xue *et al.* (2021) studied the problem

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of data retrieval based on IFSs. Lei *et al.* (2020) defined the intuitionistic fuzzy Taxonomy method. Zhao *et al.* (2021a) improved TODIM method for IF-MAGDM based on cumulative prospect theory (CPT). Zhao *et al.* (2021b) extended CPT-TODIM method for interval-valued IF-MAGDM. In addition, scholars (Garg and Arora, 2021; Tao *et al.*, 2021; Zhang *et al.*, 2021; Mishra *et al.*, 2020) *et al.* also conducted related studies on IFSs. Kutlu Gündoğdu and Kahraman (2019a) extended the IFSs to form spherical fuzzy sets (SFSs), in which the quantitative relations among membership, non-membership and hesitation are defined, and they satisfy $0 \leqslant \bar{\mu}^2_{Z_s}(a) + \bar{\nu}^2_{Z_s}(a) + \bar{\pi}^2_{Z_s}(a) \leqslant 1$. SFSs have a wide range of applications, such as military, game theory, etc., and also arouse a wide range of interest among scholars. In order to make SFSs work better, Kutlu Gündoğdu and Kahraman (2019a) defined distance and geometric operation. Mathew *et al.* (2020) proposed a new framework combining AHP and TOPSIS with SFSs. A new spherical fuzzy geometric average formula is proposed to calculate the weight of the spherical fuzzy criterion. Aydogdu and Gul (2020) proposed a new spherical fuzzy set entropy measure, and combined SFSs with WASPAS to evaluate the product, proving the feasibility of the method. Fernandez-Martinez and Sanchez-Lozano (2021) extended SFSs to a wider range of contexts constituting a new field in the context of AI problem studies, thereby expanding the scope for membership levels defined in imprecise cases. In addition, a lot of scholars (Ullah *et al.*, 2018; Kutlu Gündoğdu and Kahraman, 2019b; Zeng *et al.*, 2019; Ashraf *et al.*, 2019) have also carried out related research on it.

Taxonomy was proposed in 1763 and subsequently extended by a Polish mathematical group, and introduced as a means of classifying and determining levels of development (Jurkowska, 2014; Bienkowska, 2013). This method is very useful for classifying, categorizing, and comparing various methods to evaluate the advantages of the attributes of the study (Hellwing, 1968a,b). In recent years, some scholars have applied this method to decision analysis under some circumstances. For example, Xiao *et al.* (2020) combined the Taxonomy method with IFSs to solve the selection problem of green supply chain, and proposed an objective weighting method to improve the effectiveness of the algorithm. Wei *et al.* (2020) applied Taxonomy to select and rank low-carbon tourism destinations based on the Pythagorean fuzzy environment. He *et al.* (2019) combined Taxonomy with Pythagorean 2-Tuple linguistic classification method to select the provision of medical devices, and also adopted comparative analysis to prove the practicality of this method. These examples also prove that this method can be combined with other environments and provides a better decision method for solving MAGDM problems in other environments.

According to the existing literature on the study of SFSs, we have not found a method to use Taxonomy to solve the problem of MAGDM in the background of SFSs. Therefore, it is necessary to combine SFSs and Taxonomy to solve the MAGDM problem in this paper, which will provide a new method to solve the MAGDM problem in SFSs. This paper uses case analysis to carry on the concrete calculation, and also makes the relative comparison with the other methods which have been proved in this environment to confirm the practicability of this method. To this end, this paper has the following research ideas: (1) Use SFSs to express the decision maker's (DM) overall evaluation of the method. (2) Combine Taxonomy method with SFSs, and present the specific calculation process. (3) Take car rental as an example to present the actual operation method of the algorithm. (4) Compare and verify the method in this paper with the existing method in this environment.

This paper is structured as follows: Firstly, SFSs and Taxonomy methods are briefly introduced and their applications are introduced. Secondly, in order to make readers better understand the method, we listed the formulas and calculation steps related to SFS and Taxonomy in this part. Later, we used the example to carry out specific operations. In order to verify the correctness of this method, we used the existing SF-VIKOR and SF-TOPSIS methods for verification. Finally, we compare and summarize the methods.

2. Preliminaries

2.1. *Spherical Fuzzy Sets*

Definition 2.1.1 (Kutlu Gündoğdu and Kahraman, 2019b). The definition of an SFSs, each a to Z_s below represents our membership degree ($\bar{\mu}_{Z_s}(a)$), non-membership degree ($\bar{\nu}_{Z_s}(a)$) and hesitation number ($\bar{\pi}_{Z_s}(a)$), The relationship between them satisfies the following formula

$$Z_s = \{a(\bar{\mu}_{Z_s}(a), \bar{\nu}_{Z_s}(a), \bar{\pi}_{Z_s}(a)) \mid a \in A\}, \tag{1}$$

where $\bar{\mu}_{Z_s} : A \to [0, 1]$, $\bar{\nu}_{Z_s} : A \to [0, 1]$, $\pi_{Z_s} : A \to [0, 1]$. In addition, they will also need to satisfy $0 \leqslant \bar{\mu}^2_{Z_s}(a) + \bar{\nu}^2_{Z_s}(a) + \bar{\pi}^2_{Z_s}(a) \leqslant 1$, $\forall a \in A$.

Definition 2.1.2 (Kutlu Gündoğdu and Kahraman, 2019b). Some basic operations about SFSs.

(i) Add operation

$$X_s \oplus Y_s = \{(\bar{\mu}^2_{X_s} + \bar{\mu}^2_{Y_s} - \bar{\mu}^2_{X_s}\bar{\mu}^2_{Y_s})^{\frac{1}{2}}, \bar{\nu}_{X_s}\bar{\nu}_{Y_s}, ((1 - \bar{\mu}^2_{Y_s})\bar{\pi}^2_{X_s} \\ + (1 - \bar{\mu}^2_{X_s})\bar{\pi}^2_{Y_s} - \bar{\pi}^2_{X_s}\bar{\pi}^2_{Y_s})^{\frac{1}{2}}\}. \tag{2}$$

(ii) The multiplication

$$X_s \otimes Y_s = \{\bar{\mu}_{X_s}\bar{\mu}_{Y_s}, (\bar{\nu}^2_{X_s} + \bar{\nu}^2_{Y_s} + \bar{\nu}^2_{X_s}\bar{\nu}^2_{Y_s})^{\frac{1}{2}}, ((1 - \bar{\nu}^2_{X_s})\bar{\pi}^2_{X_s} \\ + (1 - \bar{\mu}^2_{X_s})\bar{\pi}^2_{Y_s} - \bar{\pi}^2_{X_s}\bar{\pi}^2_{Y_s})^{\frac{1}{2}}\}. \tag{3}$$

(iii) Multiplication by a scalar

$$\tau Z_s = \{(1 - (1 - \bar{\mu}^2_{Z_s})^{\tau})^{\frac{1}{2}}, \bar{\nu}^{\tau}_{X_s}, \\ ((1 - \bar{\mu}^2_{X_s})^{\tau} - (1 - \bar{\mu}^2_{X_s} - \bar{\pi}^2_{X_s})^{\tau})^{\frac{1}{2}}\}, \quad \tau > 0. \tag{4}$$

(iv)

$$X_s^{\tau} = \left\{\bar{\mu}_{X_s}, \left(1-\left(1-\bar{\nu}_{X_s}^2\right)^{\tau}\right)^{\frac{1}{2}}, \left(\left(1-\bar{\nu}_{X_s}^2\right)^{\tau}-\left(1-\bar{\nu}_{X_s}-\bar{\pi}_{X_s}^2\right)^{\tau}\right)^{\frac{1}{2}}\right\}, \quad \tau > 0. \tag{5}$$

Definition 2.1.3. For any set of fuzzy numbers $X_s = (\bar{\mu}_{X_s}, \bar{\nu}_{X_s}, \bar{\pi}_{X_s})$ and $Y_s = (\bar{\mu}_{Y_s}, \bar{\nu}_{Y_s}, \bar{\pi}_{Y_s})$, this is true for $\tau, \tau_1, \tau_2 \geqslant 0$.

(i) $X_s \oplus Y_s = X_s \oplus Y_s,$ (6)

(ii) $X_s \otimes Y_s = X_s \otimes Y_s$ (7)

(iii) $\tau_1 X_s \otimes \tau_2 X_s = (\tau_1 + \tau_2) X_s,$ (8)

(iv) $\tau(X_s \oplus Y_s) = \tau X_s \oplus \tau Y_s,$ (9)

(v) $(X_s \otimes Y_s)^{\tau} = X_s^{\tau} \otimes Y_s^{\tau},$ (10)

(vi) $X_s^{\tau_1} \otimes X_s^{\tau_2} = X_s^{\tau_1+\tau_2}.$ (11)

Definition 2.1.4 (Kutlu Gündoğdu and Kahraman, 2020, 2019c). Spherical Weighted Arithmetic Mean (SWAM) and Spherical Weighted Geometric Mean (SWGM).

$$\begin{aligned} &SWAM_{\delta}(Z_{s_1}, Z_{s_2}, \ldots\cdots, Z_{s_n}) \\ &\quad = \delta_1 Z_{s_1} + \delta_2 Z_{s_2} + \cdots + \delta_n Z_{s_n} = \left\{\left[1-\prod_{i=1}^{n}\left(1-\bar{\mu}_{Z_{s_i}}^2\right)^{\delta_i}\right]^{\frac{1}{2}}, \prod_{i=1}^{n}\bar{\nu}_{Z_{s_i}}^{\delta_i}, \right. \\ &\quad \left.\left[\prod_{i=1}^{n}\left(1-\bar{\mu}_{Z_{s_i}}^2\right)^{\delta_i} - \prod_{i=1}^{n}\left(1-\bar{\mu}_{Z_{s_i}}^2-\bar{\pi}_{Z_{s_i}}^2\right)^{\delta_i}\right]^{\frac{1}{2}}\right\}, \end{aligned} \tag{12}$$

where $\delta_i \in [0, 1]$; $\sum_{i=1}^{n} \delta_i = 1$.

$$\begin{aligned} &SWAM_{\delta}(Z_{s_1}, Z_{s_2}, \ldots, Z_{s_n}) \\ &\quad = Z_{s_1}^{\delta_1} + Z_{s_2}^{\delta_2} + \cdots + Z_{s_n}^{\delta_n} = \left\{\prod_{i=1}^{n}\bar{\mu}_{Z_{s_i}}^{\delta_i}\left[1-\prod_{i=1}^{n}\left(1-\bar{\nu}_{Z_{s_i}}^2\right)^{\delta_i}\right]^{\frac{1}{2}}, \right. \\ &\quad \left.\left[\prod_{i=1}^{n}\left(1-\bar{\nu}_{Z_{s_i}}^2\right)^{\delta_i} - \prod_{i=1}^{n}\left(1-\bar{\nu}_{Z_{s_i}}^2-\bar{\pi}_{Z_{s_i}}^2\right)^{\delta_i}\right]^{\frac{1}{2}}\right\}. \end{aligned} \tag{13}$$

Definition 2.1.5 (Kutlu Gündoğdu and Kahraman, 2019a, 2019d). The calculation formula of the score function and the accuracy function is given below

$$Score(X_s) = (\bar{\mu}_{X_s} - \bar{\pi}_{X_s})^2 - (\bar{\nu}_{X_s} - \bar{\pi}_{X_s})^2. \tag{14}$$

The score function is used to compare the size of two fuzzy numbers. If the scoring functions are equal, then compare the calculations and compare the accuracy functions.

$$Accuracy(X_s) = (\bar{\mu}_{X_s})^2 + (\bar{\nu}_{X_s})^2 + (\bar{\pi}_{X_s})^2. \tag{15}$$

Note that $X_s < Y_s$ if and only if

(i) $Score(X_s) < Score(Y_s)$ or
(ii) $Score(X_s) = Score(Y_s)$ and $Accuracy(X_s) < Accuracy(Y_s)$.

Definition 2.1.6 (Szmidt and Kacprzyk, 2000). Euclidean distance formula:

$$d(X_s, Y_s) = \sqrt{\frac{1}{2n}\sum_{i=1}^{n}\big((\mu_{X_s} - \mu_{Y_s})^2 + (\nu_{X_s} - \nu_{Y_s})^2 + (\pi_{X_s} - \pi_{Y_s})^2\big)}. \tag{16}$$

2.2. *The Taxonomy Method*

Taxonomy was proposed in 1763, subsequently extended by a Polish mathematical group, and introduced as a means of classifying and determining levels of development (Jurkowska, 2014; Bienkowska, 2013). The classical Taxonomy method is given as follows.

Step 1. Calculate the mean and standard deviation of attributes:

$$\bar{a}_j = \frac{1}{m}\sum_{i=1}^{m} a_{ij}; \quad j = 1, 2, \dots, n, \tag{17}$$

$$S_{\hat{j}} = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(a_{ij} - \bar{a}_j)^2}; \quad j = 1, 2, \dots, n. \tag{18}$$

Step 2. Because in matrix decision making alternative solutions have different measurement scales in attributes, this stage is for balancing its different units, so the following formula is used to achieve this goal (Hellwing, 1968a, 1968b, 1968c).

$$L_{ij} = \frac{a_{ij} - \bar{a}_j}{S_{\hat{j}}}; \quad i = 1, \dots, m, \ j = 1, \dots, n. \tag{19}$$

Step 3. Calculate the distance of each alternative relative to the other alternatives using the formula below (Hellwing, 1968a, 1968b, 1968c).

$$P_{ab} = \sqrt{\sum_{j=1}^{n}(l_{aj} - l_{bj})^2}, \tag{20}$$

where a and b represent the alternatives being evaluated in order to facilitate the comparison of the two alternatives, and the following composite distance matrix can be obtained:

$$P = \begin{bmatrix} p_{11} & \cdots & p_{1j} & \cdots & p_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ p_{i1} & \cdots & p_{ij} & \cdots & p_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ p_{m1} & \cdots & p_{mj} & \cdots & p_{mn} \end{bmatrix}_{m\times n}; \quad i = 1, \dots, m, \ j = 1, \dots, n. \tag{21}$$

Step 4. Calculate the mean and standard deviation of the minimum distance in each row according to the calculation formula

$$o' = \frac{1}{m}\sum_{i=1}^{m} o_{\hat{i}}, \tag{22}$$

$$S_{\widehat{o}} = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(o_{\hat{i}} - o')^2}. \tag{23}$$

In this calculation, $o_{\hat{i}}$ indicates the optimal distance of each row. Then the formula (23) is used to determine the range that the composite distance matrix should meet.

$$o = o' \pm 2S_{\widehat{0}}. \tag{24}$$

If every row has a value that doesn't fall within this range, it will not work, and the mean and standard deviation of each row will need to be calculated again.

Step 5. By the standardized matrix calculation development pattern

$$L_{io} = \sqrt{\sum_{j=1}^{n}(L_{ij} - L_{0j})^2}; \quad i = 1, \dots, m, \tag{25}$$

where L_{0j} represents the ideal value of the jth attribute, depending on whether the attribute is benefit type or negative type. L_{ij} represents the standard value of the jth attribute in the ith choice.

Step 6. Calculated the height of development

$$L_O = \bar{L}_{io} + 2S_{L_{io}}. \tag{26}$$

Then, calculate the final progression order using the following formula:

$$F_i = \frac{L_{io}}{L_o}; \quad i = 1, \dots, m. \tag{27}$$

2.3. *The Taxonomy Method with SFSs*

In this section, we combine Taxonomy method with SFS (SF-Taxonomy) method to solve the problem of MAGDM. Let $L = \{L_1, L_2, \dots, L_m\}$ be a set of alternatives, $P = \{P_1, P_2, \dots, P_n\}$ becomes a set of properties. $w = \{w_1, w_2, \dots, w_i\}$ is the set of weights for each attribute, where $\sum_{i=1}^{n} w_i = 1$. For a MAGDM problem, there are k experts for evaluation, and an expert set $L^{(k)}$ is formed, δ_i is the weight of the expert, where satisfies $\sum_{i=1}^{n} \delta_i = 1$. The steps are given below.

Step 1. Building a decision matrix

$$L^{(k)} = \left[L_{ij}^{k}\right]_{m\times n} = \begin{bmatrix} l_{11}^{k} & l_{12}^{k} & \cdots & l_{1n}^{k} \\ l_{21}^{k} & l_{22}^{k} & \cdots & l_{2n}^{k} \\ \vdots & \vdots & \ddots & \vdots \\ l_{m1}^{k} & l_{m2}^{k} & \cdots & l_{mn}^{k} \end{bmatrix}_{m\times n}, \quad i = 1, 2, \dots, m, \ j = 1, 2, \dots, n.$$

Step 2. Convert the cost attribute to the benefit attribute, for example, given a cost type fuzzy number

$$L_{ij} = (\mu_{ij}, v_{ij}, \pi_{ij}), \text{ we can get the fuzzy number of its benefit}$$
$$L_{ij} = (v_{ij}, \mu_{ij}, \pi_{ij}).$$

Step 3. The decision matrices are aggregated using the SWAM operator in conjunction with the expert weights.

Step 4. The entropy weight method is used to calculate the weight of attributes.

(1) The scoring function of the standard matrix is calculated, and the matrix obtained is normalized by the following formula:

$$\bar{L}_{ij} = \frac{score(l_{ij})}{\sum_{i=1}^{n} score(l_{ij})}; \quad j = 1, \dots, n. \tag{28}$$

(2) Calculate the degree of entropy

$$\hat{E}_j = -\frac{1}{\ln n} \sum_{i=1}^{n} \bar{l}_{ij}; \quad j = 1, \dots, n, \ 0 \leqslant \hat{E}_j \leqslant 1. \tag{29}$$

(3) Calculate the rate of degree of entropy (D_i), and then get the weights of attribute

$$D_j = 1 - \widehat{E}_j; \quad j = 1, \dots, n, \tag{30}$$

$$w_j = \frac{D_j}{\sum_{j=1}^{n} D_j}. \tag{31}$$

Step 5. The spherical fuzzy composite distance matrix is calculated (*SFCDM*).

$$SFCDM = \sum_{j=1}^{n} w_j \left(d\left((\mu_{ij}, v_{ij}, \pi_{ij}), (\mu_{kj}, v_{kj}, \pi_{kj})\right)\right). \tag{32}$$

Step 6. Select the minimum value of each row of SFCDM matrix, and calculate their mean ($SF\bar{O}$) and variance (S_{SFO}). From this we can get their online and offline.

$$SF\bar{O} = \frac{1}{m}\sum_{i=1}^{m} SFO_i, \tag{33}$$

$$S_{SFO} = \sqrt{\frac{1}{m}(SFO_i - SF\bar{O})^2}. \tag{34}$$

Step 7. Obtain the spherical fuzzy positive ideal solution (SFPIS) of each alternative

$$SFPIS = \left(\max_i \mu_{ij}, \min_i v_{ij}, \min_i \pi_{ij}\right). \tag{35}$$

Step 8. Calculate the development pattern (*SFDP*), from which you can derive the relevant matrix

$$SFDP = \sum_{j=1}^{n} w_j \left(d(SFPIS, SFL_i)\right), \quad i = 1, \dots, m. \tag{36}$$

Step 9. Calculate the average value and upper limit (*SFHLD*), from which you can get the final scheme value (*SFDA*). The minimum value is the optimal calculation scheme:

$$SFHLD = SFD\bar{P} + 2S_{SFDP}, \tag{37}$$

$$SFDA = \frac{SFDP}{SFHLD}. \tag{38}$$

3. Case Analysis

A company needs to rent a car for a major event, and there are four types of car rental companies that can offer this service. $L = \{L_1, L_2, L_3, L_4\}$ forms a collection of alternative firms. We measured the vehicles provided by these companies using four attributes: cost (U_1), endurance time (U_2), company distance (U_3), and service (U_4), among which U_1 and U_3 are cost-type attributes, while the rest are benefit attributes, the attribute weight is unknown. There are three experts who form Expert Set $E = \{E_1, E_2, E_3\}$ to score them, among which the expert weights are 0.41, 0.32, 0.27, respectively. Based on their assessment, three decisions were made in $L^{(k)}$, proof of the decision was made by the k decision maker.

Table 1
Decision matrix by DM_1.

	U_1	U_2	U_3	U_4
L_1	(0.25, 0.31, 0.12)	(0.27, 0.39, 0.25)	(0.34, 0.23, 0.52)	(0.31, 0.24, 0.12)
L_2	(0.11, 0.25, 0.31)	(0.11, 0.35.0.31)	(0.32, 0.35, 0.53)	(0.41, 0.33, 0.65)
L_3	(0.53, 0.32, 0.25)	(0.35, 0.53, 0.47)	(0.220.38, 0.35)	(0.33, 0.12, 0.42)
L_4	(0.01, 0.23, 0.23)	(0.36, 0.47, 0.22)	(0.32, 0.53, 0.32)	(0.53, 0.41, 0.23)

Table 2
Decision matrix by DM_2.

	U_1	U_2	U_3	U_4
L_1	(0.43, 0.22, 0.22)	(0.27, 0.33, 0.31)	(0.42, 0.33, 0.25)	(0.45, 0.38, 0.37)
L_2	(0.53, 0.32, 0.39)	(0.45, 0.23.0.13)	(0.42, 0.38, 0.36)	(0.59, 0.15, 0.32)
L_3	(0.43, 0.52, 0.41)	(0.58, 0.27, 0.42)	(0.55, 0.39, 0.43)	(0.47, 0.48, 0.53)
L_4	(0.28, 0.05, 0.43)	(0.43, 0.32, 0.42)	(0.02, 0.42, 0.54)	(0.35, 0.45, 0.23)

Table 3
Decision matrix by DM_3.

	U_1	U_2	U_3	U_4
L_1	(0.39, 0.43, 0.33)	(0.45, 0.34, 0.22)	(0.46, 0.31, 0.51)	(0.46, 0.32, 0.19)
L_2	(0.35, 0.16, 0.27)	(0.68, 0.42.0.31)	(0.33, 0.58, 0.31)	(0.35, 0.35, 0.22)
L_3	(0.13, 0.27, 0.35)	(0.53, 0.33, 0.45)	(0.53, 0.45, 0.25)	(0.42, 0.34, 0.42)
L_4	(0.35, 0.54, 0.28)	(0.48, 0.44, 0.52)	(0.32, 0.31, 0.32)	(0.47, 0.33, 0.41)

Table 4
Decision matrix by DM_1.

	U_1	U_2	U_3	U_4
L_1	(0.31, 0.25, 0.12)	(0.27, 0.39, 0.25)	(0.23, 0.34, 0.52)	(0.31, 0.24, 0.12)
L_2	(0.25, 0.11, 0.31)	(0.11, 0.35.0.31)	(0.35, 0.32, 0.53)	(0.41, 0.33, 0.65)
L_3	(0.32, 0.53, 0.25)	(0.35, 0.53, 0.47)	(0.38, 0.22, 0.35)	(0.33, 0.12, 0.42)
L_4	(0.23, 0.01, 0.23)	(0.36, 0.47, 0.22)	(0.53, 0.32, 0.32)	(0.53, 0.41, 0.23)

Step 1. A fuzzy evaluation matrix is given

$$L_p = [L_{ij}^p]_{m\times n} = (l_{\mu_{ij}^p}, l_{\nu_{ij}^p}, l_{\pi_{ij}^p}), \quad i = 1, 2, \dots, m, \ j = 1, 2, \dots, n$$

represents the evaluation of the pth decision maker for the M_j criterion of plan W_i in SFSs, as below Tables 1–3.

Step 2. To transform the cost-type index into the benefit-type index, as shown in Tables 4–6.

Step 3. The above decision matrix is aggregated using the SWAM operator to obtain Table 7.

Table 5
Decision matrix by DM_2.

	U_1	U_2	U_3	U_4
L_1	(0.22, 0.43, 0.22)	(0.27, 0.33, 0.31)	(0.33, 0.42, 0.25)	(0.45, 0.38, 0.37)
L_2	(0.32, 0.53, 0.39)	(0.45, 0.23.0.13)	(0.38, 0.42, 0.36)	(0.59, 0.15, 0.32)
L_3	(0.52, 0.43, 0.41)	(0.58, 0.27, 0.42)	(0.39, 0.55, 0.43)	(0.47, 0.48, 0.53)
L_4	(0.05, 0.28, 0.43)	(0.43, 0.32, 0.42)	(0.42, 0.02, 0.54)	(0.35, 0.45, 0.23)

Table 6
Decision matrix by DM_3.

	U_1	U_2	U_3	U_4
L_1	(0.43, 0.39, 0.33)	(0.45, 0.34, 0.22)	(0.31, 0.46, 0.51)	(0.46, 0.32, 0.19)
L_2	(0.16, 0.35, 0.27)	(0.68, 0.42.0.31)	(0.58, 0.33, 0.31)	(0.35, 0.35, 0.22)
L_3	(0.27, 0.13, 0.35)	(0.53, 0.33, 0.45)	(0.45, 0.53, 0.25)	(0.42, 0.34, 0.42)
L_4	(0.54, 0.35, 0.28)	(0.48, 0.44, 0.52)	(0.31, 0.32, 0.32)	(0.47, 0.33, 0.41)

Table 7
The overall decision matrix.

	U_1	U_2	U_3	U_4
L_1	(0.33, 0.34, 0.23)	(0.33, 0.36, 0.26)	(029, 0.39, 0.45)	(0.40, 0.39, 0.25)
L_2	(0.26, 0.25, 0.33)	(0.47, 0.32.0.28)	(0.44, 0.35, 0.42)	(0.47, 0.44, 0.49)
L_3	(0.39, 0.34, 0.35)	(0.49, 0.38, 0.45)	(0.40, 0.37, 0.36)	(0.41, 0.39, 0.46)
L_4	(0.33, 0.08, 0.32)	(0.42, 0.41, 0.40)	(0.45, 0.13, 0.41)	(0.47, 0.45, 0.29)

Table 8
The *SFCDM*.

	L_1	L_2	L_3	L_4
L_1	–	0.1058	0.1396	0.1487
L_2	0.10583	–	0.1181	0.1234
L_3	0.1396	0.1181	–	0.1190
L_4	0.1487	0.1234	0.1190	–

Step 4. Equations (28)–(31) were used to calculate the objective weight

$$\varpi_1 = 0.3798, \qquad \varpi_2 = 0.5413, \qquad \varpi_3 = 0.0243, \qquad \varpi_4 = 0.0546.$$

Step 5. *SFCDM* was calculated by equations (32), as shown in Table 8.

Step 6. Find the minimum value of each row of *SFCDM* matrix (SFO_i), calculate its mean value ($SF\bar{O}$) and its variance (S_{SFO}).

$$SFO_1 = 0.1058, \qquad SFO_2 = 0.1058, \qquad SFO_3 = 0.1181, \qquad SFO_4 = 0.1190,$$
$$SF\bar{O} = 0.1122, \qquad S_{SFO} = 0.0064.$$

Table 9
The SFPIS of each alternative.

U_1	U_2	U_3	U_4
(0.39, 0.08, 0.23)	(0.49, 0.32, 0.26)	(0.45, 0.13, 0.36)	(0.47, 0.39.0.25)

Table 10
The SFDA.

L_1	L_2	L_3	L_4
0.7669	0.4757	0.8867	0.5433

Step 7. From $SFDP_i$ and S_{SFO}, it can be concluded that its upper and lower lines are

$$SFO = SF\bar{O} \pm S_{SFO} = 0.1122 \pm 0.0064.$$

Step 8. Obtain the optimal distance under fuzzy environment, as shown in Table 9.

Step 9. Compute the development pattern ($SFDP_i$).

$$SFDP_1 = 0.1418, \quad SFDP_2 = 0.088, \quad SFDP_3 = 0.1639, \quad SFDP_4 = 0.1004.$$

Step 10. The mean value and variance of SFDP can be calculated.

$$SFDP\bar{O} = 0.1234, \qquad S_{SFDP} = 0.0307.$$

Similarly, the upper limit of *SFDP* can also be obtained by calculation.

$$SFHLD = 0.1849.$$

Step 11. The *SFDA* was calculated in Table 10.

From the final value of *SFDA* obtained above, we can get the final scheme ordering as $L_2 > L_4 > L_1 > L_3$. From sorting, we can get L_2 as the optimal scheme we got, so we finally choose L_2 as the optimal provider in this activity.

4. Comparative Analysis

In order to verify the correctness of the SF-Taxonomy method, we adopted the examples and original data previously given in the paper, and adopted the SF-TOPSIS (Kutlu Gündoğdu and Kahraman, 2021) and SF-VIKOR (Sharaf, 2021) methods that have been confirmed by scholars for verification. The results obtained by them are compared with those obtained by the method presented in this paper.

Table 11
The overall weight matrix.

	U_1	U_2	U_3	U_4
L_1	(0.21, 0.66, 0.13)	(0.19, 0.70, 0.16)	(0.24, 0.64, 0.30)	(0.24, 0.13, 0.15)
L_2	(0.21, 0.52, 0.21)	(0.26, 0.68.0.18)	(0.21, 0.73, 0.29)	(0.41, 0.33, 0.65)
L_3	(0.27, 0.63, 0.21)	(0.29, 0.72, 0.30)	(0.26, 0.73, 0.24)	(0.33, 0.12, 0.42)
L_4	(0.13, 0.52, 0.19)	(0.25, 0.74, 0.25)	(0.16, 0.76, 0.25)	(0.53, 0.41, 0.23)

Table 12
The score function of the overall weight matrix.

	U_1	U_2	U_3	U_4
L_1	−0.233	−0.299	−0.136	0.132
L_2	−0.071	−0.159	−0.264	0.147
L_3	−0.083	−0.145	−0.213	0.101
L_4	−0.149	−0.240	−0.360	0.204

Table 13
The SFPIS and SFNIS.

	U_1	U_2	U_3	U_4
SFNIS	(0.37, 0.65, 0.23)	(0.33, 0.81, 0.28)	(0.46, 0.71, 0.20)	(0.42, 0.36, 0.27)
SFPIS	(0.54, 0.56, 0.15)	(0.55, 0.63, 0.30)	(0.57, 0.56, 0.23)	(0.55, 0.48, 0.26)

Table 14
The distance between the overall weight matrix and
the SFPIS and SFNIS.

	$D_E(L_{ij}, X_j^-)$	$D_E(L_{ij}, X_j^*)$
L_1	0.033	0.078
L_2	0.078	0.081
L_3	0.068	0.074
L_4	0.074	0.080

4.1. *Compared with SF-TOPSIS Method*

Step 1. The overall weight matrix is calculated and the SWAM operator is used for aggregation (see Table 11).

Shep 2. Calculate the score function of the overall weight matrix (see Table 12).

Step 3. The optimal distance (*SFPIS*) and the worst distance (*SFNIS*) are calculated according to the score function (see Table 13).

Step 4. Calculate the distance between the overall weight matrix and the *SFPIS* and the *SFNIS* (see Table 14).

Step 5. Calculate the closeness ratio of each alternative (*SFCR*) (see Table 15).

Table 15
The closeness ratio of each alternative (*SFCR*).

	Closeness ratio
L_1	0.2947
L_2	0.4893
L_3	0.4789
L_4	0.4807

Table 16
The SFPIS and SFNIS.

	U_1	U_2	U_3	U_4
SFNIS	(0.24,0.36,0.34)	(0.33,0.41,0.45)	(0.27,0.43,0.45)	(0.40,0.45,0.49)
SFPIS	(0.43,0.18,0.23)	(0.39,0.32,0.26)	(0.45,0.28,0.36)	(0.47,0.39,0.25)

Table 17
The weight distance $\bar{R}_{ij}$.

	U_1	U_2	U_3	U_4
$\tilde{R}_{1j}$	0.1977	0.3382	0.0100	0.0141
$\tilde{R}_{2j}$	0.1877	0.0558	0.0168	0.0523
$\tilde{R}_{3j}$	0.2805	0.4049	0.0117	0.0483
$\tilde{R}_{4j}$	0.2836	0.3740	0.0229	0.0160

Table 18
The separation measures $\bar{R}$ and $\bar{Q}_i$.

	P_1	P_2	P_3	P_4
$\bar{R}$	0.3382	0.1877	0.4049	0.3740
$\bar{S}$	0.5599	0.3127	0.7455	0.6966

According to the above calculation results of SF-TOPSIS method with the same data, we can get the final decision ranking of the scheme is $L_2 > L_4 > L_3 > L_1$. From the ranking of the results, it is not difficult to see that L_2 is the optimal decision of the scheme, so we will choose L_2 as the best choice for the company's activities in the end.

4.2. *Comparison with SF-VIKOR Method*

As above, we will also directly show the calculation results of SF-VIKOR method here.

Step 1. The decision matrix is aggregated using the SWAM operator.

Step 2. The SFPIS and SFNIS are obtained from the aggregation matrix (see Table 16).

Step 3. The weight distance $\bar{R}_{ij}$ is calculated by combining the attribute weight (see Table 17).

Step 4. The separation measures $\bar{R}$ and $\bar{Q}_i$ can be obtained (see Table 18).

Table 19
The $\bar{S}^{+}$, $\bar{S}^{-}$ and $\bar{R}^{+}$, $\bar{R}^{-}$.

$\bar{R}^{+}$	0.1877	$\bar{R}^{-}$	0.4049
$\bar{S}^{+}$	0.3127	$\bar{S}^{-}$	0.7455

Table 20
The $\bar{Q}_i$.

$\bar{Q}_1$	$\bar{Q}_2$	$\bar{Q}_3$	$\bar{Q}_4$
0.6320	0.0000	1.0000	0.8723

Table 21
The comparative analysis result.

Methods	Consequences
SF-TAXONOMY	$L_2 > L_4 > L_1 > L_3$
SF-TOPSIS	$L_2 > L_4 > L_3 > L_1$
SF-VIKOR	$L_2 > L_3 > L_1 > L_4$

Step 5. Sort $\bar{R}$ and $\bar{S}$, then determine $\bar{S}^{+}$, $\bar{S}^{-}$ and $\bar{R}^{+}$, $\bar{R}^{-}$ (see Table 19).

Step 6. Finally, $\bar{Q}_i$ can be calculated to obtain scheme ordering. Take $\nu = 0$ (Opricovic, 1998) in the following calculation (see Table 20).

According to $\bar{Q}_i$, it can be concluded that its ranking is $\bar{Q}_2 < \bar{Q}_3 < \bar{Q}_1 < \bar{Q}_4$, so the ranking of the scheme is $L_2 > L_3 > L_1 > L_4$. Therefore, it can be seen that Z_2 is the optimal scheme.

4.3. *Comparative Analysis*

In order to more clearly and intuitively see the results of these two methods and the SF-Taxonomy method, the results are shown in Table 21.

In order to improve the accuracy of comparison, we used the same case above to conduct a comparative study on the SF-TOPSIS method and the SF-VIKOR method, and found that the SF-Taxonomy method formed by applying the Taxonomy method in the SFS environment in this paper was objective and effective. The optimal solution is consistent when the optimal decision is made. There was little difference in the rankings for the rest. In the research of SF-Taxonomy method, entropy weight method is introduced to calculate the objective weight because the attribute weight is unknown, so as to make the result more accurate and objective.

5. Conclusion

Through the study of SFSs by scholars and the application of Taxonomy method in other backgrounds, this paper combines Taxonomy method with SFSs to form a new method to solve the multi-attribute decision problem in SFSs environment. In this paper, the concrete steps of SF-Taxonomy method are given. In order to make readers understand the method more clearly, the paper also gives the relevant calculation example analysis. In order to verify the correctness of such methods, the SF-TOPSIS method and the SF-VIKOR method, which have been confirmed by scholars, were compared in the following part of the paper, and relevant comparative analysis was made. The optimal scheme obtained by them in comparison is consistent, which confirms the correctness of this method. In the future, this approach could also have important applications in other contexts.

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