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Multicriteria Decision Making Using SR-Fuzzy Sets

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Abstract

In this study, we introduce and explore square-root fuzzy sets (SR-Fuzzy sets), a novel extension within the realm of fuzzy set theory. We begin by establishing a comparative analysis between SR-Fuzzy sets and two well-known fuzzy set models: Intuitionistic Fuzzy Sets (IFS) and Pythagorean Fuzzy Sets (PFS). This comparison highlights the unique characteristics and mathematical structure of SR-Fuzzy sets. A particular focus is placed on the complement operator, which plays a critical role in the logical framework and functional behavior of SR-Fuzzy sets. Additionally, we define a set of fundamental mathematical operations specific to SR-Fuzzy sets, laying the groundwork for further theoretical development. To facilitate practical applications, an accuracy function is formulated, along with a scoring function that enables effective ranking of SR-Fuzzy sets. We also investigate the use of Euclidean distance as a metric for measuring dissimilarity between two SR-Fuzzy sets. Building on these foundations, we propose a novel SR-Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) approach, tailored for addressing multiple-criteria decision-making (MCDM) problems. The robustness and applicability of the proposed methodology are illustrated through a comprehensive, real-world numerical example, thereby demonstrating its relevance, practicality, and potential advantages over existing methods.

Keywords: SR-Fuzzy sets, Euclidean distance, Multicriteria decision making, complement operator, fuzzy decision-making

INTRODUCTION

Fuzzy orthopair sets consist of values in the unit interval {μ(x), ν(x)}, where one value for support for inclusion in the fuzzy set and a different value suggests resistance to membership. It is observed that the total squaring of the support and opposite is bound with the help of one for classic intuitionistic fuzzy sets, but not by one for Pythagorean fuzzy sets(PFS), the second sort. Q-rung orthopair fuzzy sets, known as the General class of these sets, were presented by Yager (2017) [1]. In these sets, the qth power sum of the side against and the qth degree of favor for the bonded. He pointed out that as q rises, the universe of admissible orthopairs expands as well, allowing the user more leeway in expressing their opinions regarding membership grade.

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Aggregation operators of PFS were defined by Yager (2014) [2]. He acknowledged the MCDM issue because of the way PMGs will be used to communicate the criteria fulfillment. Zhang (2016) [3] used the notion of the similarity measure to illustrate an MCDM challenge. Pythagorean fuzzy TODIM was proposed by Ren et al. (2016) [4] for MCDM challenges. As demonstrated by Yager and Abbasov (2013) [5], PMGs are unique categories of complex numbers known as Π-i numbers. They looked at the difficulty of MCDM using PMGs, or Π-i numbers, to indicate pleasure. Pythagorean fuzzy aggregation operators were employed by Peng and Yang (2015) [6] to evaluate investments in Internet stocks. Using the PFNs, Reformat and Yager (2014) [7] produced an itemized list of the nominated films from Netflix. Intuitionistic fuzzy sets are Pythagorean fuzzy sets, and they created a historical ledger of the many kinds and their links. Gou et al. (2016) [8] defined the sequences and change values concerning PFNs as variables before analyzing the convergences of the sequences on PFNs. The continuity and derivability of Pythagorean fuzzy functions were also covered. Senapati et al. (2019) [9] proposed a Fermatean fuzzy set along with its score function and accuracy function to evaluate its ranking. He also studied the distance between two (FFS) Fermatean fuzzy sets and established a method of TOPSIS to perform decision-making in multi-criteria problems.

We also examine the SR-Fuzzy set introduced by Shami [10] in more detail. We talk about a few fundamental SR-Fuzzy set attributes. Ranks the options according to how far they are away from positive (+) Solution (PIS) and the negative (-) Solution (NIS). The best options, therefore, require the least amount of time to separate from the PIS and the greatest amount of time to separate from the NIS.

The following are the contributions made by this paper: The formal introduction to the work is provided, and Next, we define SR-fuzzy sets. We address the complement operator. The operations, scoring, and accuracy function, distance of the SR-Fuzzy set, are all defined in Sect. 2. We extend a square-root fuzzy TOPSIS approach in Sect. 3 to maybe clarify those MCDM problems for SR-Fuzzy sets. We present a helpful decision-making problem in Sect. 4 that demonstrates the provision mechanism of the recommended approach. Sect. 5 concludes with an outline and discussion of the scope of future research.

PRELIMINARIES

We quickly define certain terms used in the remaining work to make it self-sufficient.

Pythagorean Fuzzy Sets

The Pythagorean fuzzy set was introduced by Yager (2013) [11], Let Pythagorean fuzzy sets A = {(x, μA(x), νA(x)) | x ∈ X}, the νA(x) ∣ X → [0, 1]} and μA(x) ∣ X→ [0, 1]}, respectively, degree of membership and non-membership of each element x ∈ X} to the set P, and $0 \leq (\mu A(x)^2 + \nu A(x)^2 \leq 1$, for all x ∈ X. Degree of indeterminacy of x with respect to P is denoted As $\boldsymbol{\pi_p(x)} = \sqrt{(\boldsymbol{\mu_A(x)})^2 - (\boldsymbol{\nu_A(x)})^2}$ For every PFS for x ∈ X.

SR-Fuzzy Sets

Here, we introduce the idea of SR-Fuzzy sets and thoroughly examine their characteristics in this part [10].

S be a universal set μθ: S⟶[0,1] and vθ: S⟶[0,1]. Then, SR-Fuzzy set θ is defined as:

θ = {(x, μθ(x), vθ(x)) | x ∈ X}}

where μθ(x) is the membership degree and vθ(x) is the non-membership degree of x ∈ X to θ, such that

$$0 \leq (\mu\theta(x))^2 + \sqrt{\mathrm{v}\theta(\mathrm{x})} \leq 1)$$

And indeterminacy degree of x ∈ X to θ is

$$\Pi\theta\ (\mathrm{X}) = 1 - \left(\mu\theta(x)\right)^2 + \sqrt{\mathrm{v}\theta(\mathrm{x})}$$

Here $(\mu\theta(x))^2 + \sqrt{v_\theta(x)} + \mu\theta(x)) = 1$. Otherwise, $\Pi\theta$ (X) =0 whenever $(\mu\theta(x))^2 + \sqrt{v_\theta(x)} \leq 1$.

Example 1. Assume that μθ(x) = 0.4 and vθ(x) = 0.9 for X ∈ {x}. Then, θ = 0.4,0.7 is not an intuitionistic fuzzy set because 0.4 + 0.7 = 1.1>1. In contrast, θ = (0.4,0.7) is an SR-FS because $(0.4)^2 + \sqrt{0.7} \approx 0.99666 \leq 1$.

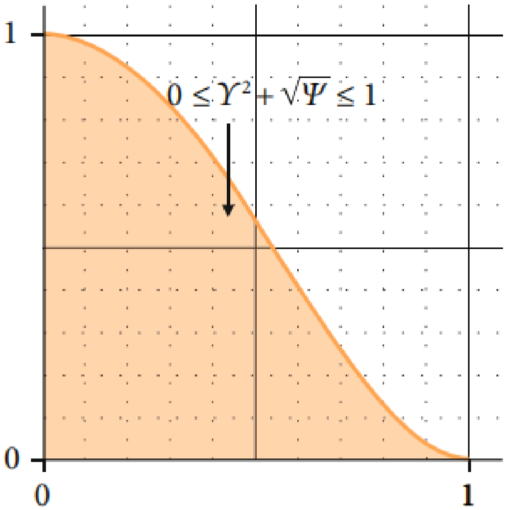

Figure 1. Graph of SR-Fuzzy membership grade.

Note that $\Pi\theta$ (X) = 0.00334, and hence, $(\mu\theta(x))^2 + \sqrt{v_\theta(x)} + \Pi\theta$ (X) =1. The Graph of SR-Fuzzy membership grades is shown in Figure 1.

Definition 1. Let $\theta_1 = (\mu_{\theta1}, v_{\theta1})$ and $\theta_2 = (\mu_{\theta2}, v_{\theta2})$ be two SR-FSs. Then $v_{\theta2}$

1. $\theta_1 = \theta_2$ If and only if $\mu_{\theta1} = \mu_{\theta2}$ and $v_{\theta1} = v_{\theta2}$
2. $_1 \geq \theta_2$ If and only if $\mu_{\theta1} \geq \mu_{\theta2}$ and $v_{\theta1} \leq v_{\theta2}$

Example 2.

1. If $\theta_1 = (.3,.8)$ and $\theta_2 = (.3,.8)$ for X= {x}, then $\theta_1 = \theta_2$
2. If $\theta_1 = (.3,.8)$ and $\theta_2 = (.1,.91)$ for X= {x}, then $\theta_2 \leq \theta_1$

Definition 2. Let $\theta_1 = (\mu_{\theta1}, v_{\theta1})$ and $\theta_2 = (\mu_{\theta2}, v_{\theta2})$ be two SR-FSs. then

1. $\theta_1 \cap \theta_2$ = (min $\{\mu_{\theta1}, v_{\theta1}\}$, max $\{\mu_{\theta2}, v_{\theta2}\}$)
2. $\theta_1 \cup \theta_2$ = (max $\{\mu_{\theta1}, v_{\theta1}\}$, min $\{\mu_{\theta2}, v_{\theta2}\}$)
3. $\theta_{1^c} = \left(\sqrt[4]{v_{\theta,1}}(\mu)^4_{\theta 1}\right)$

Note that ($\sqrt[4]{v_{\theta_1}}$ ^{2}, (μ $_{\theta1}$)^4 = $(\mu_\theta(x))^2 + {}^2\sqrt{(\mu_\theta(x)}$ ≤ 1, so θ^c is an SR-Fuzzy set. It is obvious that $((\theta^c)^c$ =

($\sqrt[4]{v_{\theta_1}}$)$^{2)}$) = ($\mu\theta$, $v\theta$).

Example 3. Assume that $\theta_1 = (\mu_{\theta1} = 0.59, v_{\theta1} = 0.42)$ and $\theta_2 = (\mu_{\theta2} = 0.56, v_{\theta2} = 0.45)$ are both SR-FSs for X = {x}. Then

1. $\theta_1 \cap \theta_2$ = (min $\{\mu_{\theta1}, v_{\theta1}\}$, max $\{\mu_{\theta2}, v_{\theta2}\}$) = (min {0.59, 0.56}, max {0.42, 0.45}) = (0.56,0.45)
2. $\theta_1 \cup \theta_2$ = (max $\{\mu_{\theta1}, v_{\theta1}\}$, min $\{\mu_{\theta2}, v_{\theta2}$) = (max {0.59, 0.56}, min {0.42, 0.45}) = (0.59,0.42)
3. θ_1^c= (0.805030, 0.121174)

Theorem 1. Let $\theta_1 = (\mu_{\theta1}, v_{\theta1})$ and $\theta_2 = (\mu_{\theta2}, v_{\theta2})$ be two SR-FSs:

1. $\theta_1 \cap \theta_2 = \theta_2 \cap \theta_1$
2. $\theta_1 \cup \theta_2 = \theta_2 \cup \theta_1$

Theorem 2. Let $\theta_1 = (\mu_{\theta1}, v_{\theta1})$, $\theta_2 = (\mu\theta, v_{\theta2})$ and $\theta_3 = (\mu_\theta, v_{\theta3})$ be three SR-FSs. Then the following properties hold:

1. $\theta_1 \cap (\theta 2 \cap \theta_3) = (\theta_1 \cap \theta_2) \cap \theta_3$
2. $\theta_1 \cup (\theta_2 \cup \theta_3) = (\theta_1 \cup \theta_2) \cup \theta_3$

Theorem 3. Let $\theta_1 = (\mu_{\theta 1}, v_{\theta 1})$ and $\theta_2 = (\mu_{\theta 2}, v_{\theta 2})$ be two SR-FSs. Then

1. $(\theta_1 \cap \theta_2) \cup \theta_2 = \theta_2$
2. $(\theta_1 \cup \theta_2) \cap \theta_2 = \theta_2$

Theorem 4. Let $\theta_1 = (\mu_{\theta 1}, v_{\theta 1})$ and $\theta_2 = (\mu_{\theta 2}, v_{\theta 2})$ be two SR-FSs. Then

1. $(\theta_1 \cap \theta_2)^C = \theta_1^C \cup \theta_2^C$
2. $(\theta_1 \cup \theta_2)^C = \theta_1^C \cap \theta_2^C$

Definition 3. Let $\theta = (\mu_\theta, v_\theta)$, $\theta_1 = (\mu_{\theta 1}, v_{\theta 1})$, and $\theta_2 = (\mu_{\theta 2}, v_{\theta 2})$ be three SR-FSs. and p be a positive real value ($p > 0$):

1. $\theta_1 + \theta_2 = (\sqrt{\mu_{\theta_1}^2 + \mu_{\theta_2}^2 - \mu_{\theta_1}^2 \mu_{\theta_2}^2}, v_{\theta_1} v_{\theta_2})$
2. $\theta_1 \times \theta_2 = (\mu_{\theta_1} \mu_{\theta_2}, (\sqrt{v_{\theta_1}} + \sqrt{v_{\theta_2}} - \sqrt{v_{\theta_1}}\sqrt{v_{\theta_2}})^2)$
3. $p^{\theta} = (\sqrt{1 - (1 - \mu^2)^p}, v_\theta^p)$
4. $\theta^p = (\mu^p, (1 - (1 - \sqrt{v_\theta})^p)^2)$

Example 4. Suppose that ($\mu_{\theta 1} = 0.44$, $v_{\theta 1} = 0.63$) and ($\mu_{\theta 2} = 0.25$, $v_{\theta 2} = 0.82$) are both SR-FSs for X ∈ {x}.

(1) $\theta_1 + \theta_2 = (\sqrt{\mu_{\theta_1}^2 + \mu_{\theta_2}^2 - \mu_{\theta_1}^2 \mu_{\theta_2}^2}, v_{\theta_1} v_{\theta_2}) =$

$(\sqrt{(0.44)^2 + (0.63)^2 - (0.44)^2 (0.25)^2}, (0.63)^2(0.82)^2) = (0.760526, 0.266875)$

(2) $\theta_1 + \theta_2 = (\mu_{\theta_1} \mu_{\theta_2}, (\sqrt{v_{\theta_1}} + \sqrt{v_{\theta_2}} - \sqrt{v_{\theta_1}}, \sqrt{v_{\theta_2}}))^2 = ((0.44)(0.25), (\sqrt{0.63} + \sqrt{0.82} - \sqrt{0.63}\sqrt{0.82})^2) = (0.11, 0.961409)$

(3) $p^{\theta} = (\sqrt{1 - (1 - \mu^2)^p}, v_\theta) = p^{\theta} = (\sqrt{1 - (1 - 0.44^2)^4}, 0.63^4) =$ $(0.759693, 0.157529)$, for p = 4.

(4) $\theta^p = (\mu^p, (1 - (1 - \sqrt{v_\theta}))^2) = (0.44^4, (1 - (1 - \sqrt{0.63}))^{4\,2}) = (0.037480, 0.998189)$, for p = 4.

Definition 4.

1. Score function of SR-FS $\theta = (\mu\theta, v\theta)$ defined as score(θ) = $\mu_\theta^2 - \sqrt{v\theta}$
2. Accuracy function SR-FS $\theta = (\mu\theta, v\theta)$ defined as accuracy(θ) = $\mu_\theta^2 + \sqrt{v\theta}$

Example 5. SR-FS $\theta = (0.4, 0.7)$, we find that score(θ) ≈ - 0.676660 and accuracy(θ) ≈ 0.996660 In particular, if $\theta = (0,1)$, then the score(θ) is -1 and if $\theta = (1,0)$, then the score(θ) is 1.

SR-FUZZY TOPSIS METHOD TO THE MCDM PROBLEM

The use of the TOPSIS approach for MCDM problems when the ranking data is given in SRFs will be examined in the present part. A PIS constantly seeks the lowest possible cost situation and the maximum value for the benefit situation. Conversely, a NIS consistently seeks the highest possible value for cost criteria and the lowest possible value for benefit criteria.

MCDM Problem with SRFs

The majority of MCDM problems involve ranking one or more options based on a variety of criteria from a collection of potential alternatives. Assume that there are m choices S_i (i = 1, 2, …, m) and n C_j

(j = 1, 2, …, n) for the stated MCDM issue under the Square-root fuzzy domain. The criteria weight vector $w = (w_1, w_2, \ldots, w_n)^T$ is certain up to expectation $0 < w_j \leq 1$, j = 1, 2, …, n, and $\sum_{j=1}^{n} wj = 1$. We use $C_j (S_i) = (u_{ij}, v_{ij})$ to indicate the values of the option Si about the criterion C_j, and $R = (C_j (S_i))_{m\times n}$ is a fuzzy decision matrix with square roots:

$$R = \left(C_j(S_i)\right)_{m\times n} = \begin{array}{c c} & \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{array}{c} S_1 \\ S_2 \\ \vdots \\ S_m \end{array} & \begin{pmatrix} (u_{11}, v_{11}) & (u_{12}, v_{12}) & \dots & (u_{1n}, v_{1n}) \\ (u_{21}, v_{21}) & (u_{22}, v_{22}) & \cdots & (u_{2n}, v_{2n}) \\ \vdots & \vdots & \ddots & \vdots \\ (u_{m1}, v_{m1}) & (u_{m2}, v_{m2}) & \cdots & (u_{mn}, v_{mn}) \end{pmatrix} \end{array} \tag{1}$$

The Decision Method

After understanding the MCDM problem using SRFs, we provide a Square-root fuzzy TOPSIS system for emulation. The recommended systems require an assistance rule that the good option should require the shortest separations, beginning with the PIS, and the furthest separations, starting with the NIS. Therefore, the SR-fuzzy PIS (SRPIS) and square-root fuzzy NIS (FFNIS) computations are the first steps in this method. Acknowledging that the choice follows the structure of SRNs as expected, we support the score function-based approach described in Definition 4 as being in line with identifying the SRPIS and the SRNIS. We use S+ to represent the SRPIS, which can be computed using the corresponding equation:

$$S^{+} = \begin{cases} {}^{max}_{\;\;i}\langle score\left(C_j(S_i)\right)\rangle \,|j = 1, 2, \ldots, n, \\ \quad if\ c_j\ is\ a\ benefit\ criterion \\ {}^{min}_{\;\;i}\langle score\left(C_j(S_i)\right)\rangle \,|j = 1, 2, \ldots, n, \\ \quad\quad if\ c_j\ is\ a\ cost\ criterion \end{cases}$$

$$= \{(u_1^+, v_1^+), (u_2^+, v_2^+), \ldots, (u_n^+, v_n^+)\} \tag{2}$$

The SRPIS S+ is an efficient solution to the MCDM problem in all other cases. Next, we continue to concentrate on the separation between each alternative and the SRPIS. In this instance

Therefore, using Eq. (3), one may determine the distance between the alternative Si and the SRPIS S+.

$$D(S_i, S^+) = \sum_{j=1}^{n} w_j\, d\left(C_j(S_i), C_j(S^+)\right)$$

$$= \sum_{j=1}^{n} w_j \sqrt{\frac{1}{2}\left[\left(a_{ij}^2 - a_j^{+2}\right)^2 + \left(\sqrt{\bar{b}_{ij}} - \sqrt{\bar{b}_j^{+}}\right)^2 + \left[\left(a_j^{+2} - a_{ij}^2\right) + \left(\sqrt{\bar{b}_j^{+}} - \sqrt{\bar{b}_{ij}}\right)\right]^2\right]}$$

$$i = 1, 2, \ldots, m \tag{3}$$

The small $D (S_i, S^+)$ gives the alternative S_i,

$$D_{min}(S_i, S^+) = {}^{\;\;min}_{1\leq i\leq m} D(S_i, S^+) \tag{4}$$

On the other hand, there's a potential that the options for the closest separation on SRPIS won't necessarily be the ones that are farthest from SRNIS. By S^-, we denote those SRNIS that can be found using the accompanying formula:

$$S^{-} = \begin{cases} {}^{max}_{\;\;i}\langle score\left(C_j(S_i)\right)\rangle \,|j = 1, 2, \ldots, n, \\ \quad if\ c_j\ is\ a\ benefit\ criterion \\ {}^{min}_{\;\;i}\langle score\left(C_j(S_i)\right)\rangle \,|j = 1, 2, \ldots, n, \\ \quad\quad if\ c_j\ is\ a\ cost\ criterion \end{cases}$$

$$= \{(u_1^-, v_1^-), (u_2^-, v_2^-), \ldots, (u_n^-, v_n^-)\} \tag{5}$$

Eq (5) makes it easy to see that the SRNIS's acquired value for each attribute is the lowest of all the possible values. Typically, those SRNIS may not exist in the helpful MCDM procedure. In particular,

The SRNIS S^-, or $S^- \notin X$, can occasionally be an impractical substitute. If not, the SRNIS STM could be the worst option compared to the MCDM issue, which is an opportunity to be eliminated using the favored technique.

From Eq. (6), the following methods can be applied to find the distance of the Si and the SRNIS S^-:

$$D(S_i, S^-) = \sum_{j=1}^{n} w_j \, d\left(C_j(S_i), C_j(S^-)\right)$$

$$= \sum_{j=1}^{n} w_j \sqrt{\frac{1}{2}\left[(a_{ij}^2 - \bar{a}_j^{-2})^2 + (\sqrt{b_{ij}} - \sqrt{\bar{b}_j^-})^2 + [(\bar{a}_j^{-2} - a_{ij}^2) + (\sqrt{\bar{b}_j^-} - \sqrt{b_{ij}})]^2\right]}$$

$$i = 1, 2, \ldots, m \quad (6)$$

The higher $D(Si, S^-)$ produces the superior alternative S_i,

$$D_{max}(S_i, S^-) = \max_{1 \le i \le m} D(S_i, S^-) \quad (7)$$

Concerning the SRPIS S^+, as shown below, we typically have trouble determining the proximity of the alternative Si using the conventional TOPSIS method:

$$RC(S_i) = \frac{D(S_i, S^-)}{D(S_i, S^-) + D(S_i, S^+)} \quad (8)$$

The best options and their positioning requests might be determined by the closeness index RC(Si) graphic. Hadi Vencheh (2014), nonetheless, suggested that when clinched alongside a scenario, relative closeness cannot reach the point where those ideal results should require. As a result, the limiting equation (i.e., Eq. (8)) is used in this specific scenario rather than the relative closeness index.

$$\zeta(S_i) = \frac{D(S_i, S^-)}{D_{max}(S_i, S^-)} - \frac{D(S_i, S^+)}{D_{mix}(S_i, S^+)} \quad (9)$$

It is known as the updated closeness to the measurement, and the degree Si is significantly apart from the SRNIS S−, while potentially being close to those SRPIS S+. $\zeta(S_i) \le 0$ The larger $\zeta(S_i)$, the unusual Si, are readily apparent. In the event when an alternate S^* materializes that satisfies the conditions that $D(S^*, S^-) = D_{max}(S_i, S^-)$ and $D(S^*, S^+) = D_{min}(S_i, S^+)$ concurrently, $\zeta(S^*) = 0$ and, thus, the choice S is the fortunate option that is closest to the SRPIS S^+ and furthest from the SRNIS S^-, respectively.

PRACTICAL EXAMPLES

Selecting the Best College for Higher Studies

Every student dreams of pursuing higher education in a college that will shape their future. A group of students from Uttarakhand is in the final year of high school and wants to choose the best college for their undergraduate studies. They form a group named "Scholars United" to research and select the most suitable college. The group narrows down their options to four colleges: SSJ Campus, Almora (S2), MBPG College, Haldwani (S3), Graphic Era University, Dehradun (S3), DSB Campus, Nainital (S4). To make an informed decision, they consider five key criteria:

Academic Staff (C1)

The quality of education heavily depends on the faculty. The students look at the number of professors with advanced degrees, their teaching experience, and their contribution to academic research. They prefer colleges with a higher number of experienced and well-qualified teachers, as they believe this will provide them with a strong academic foundation.

Scientific Research Opportunities (C2)

For students aspiring to excel in scientific fields, the availability of research opportunities is crucial. They investigate the research facilities, the number of research projects undertaken, and the college's collaboration with other research institutions. A college with a robust research program will provide them with the practical experience needed for their future careers.

Fee Structure (C3)

Finally, the students consider the affordability of the college. They analyze the tuition fees, accommodation costs, and other charges to ensure that the total cost of education fits within their budget. They understand that while a good education is invaluable, it is also important to choose a college that won't put a financial strain on their families.

Library Facilities (C4)

A well-equipped library is essential for any student. The students look into the size of the library, the variety of books and journals available, access to online databases, and the availability of study spaces. They want a college that offers extensive resources to support their academic endeavors and research.

National and International Scientific Activities (C5)

Participating in national and international scientific activities, such as conferences, seminars, and exchange programs, is important for students to broaden their horizons. They evaluate the colleges based on their involvement in such activities, as it will offer them exposure to the latest developments in their fields and networking opportunities with experts from around the world.

DESCRIPTION

Scholars United set weight vector criteria is $w = (0.2, 0.3, 0.1, 0.2, 0.2)^T$

They give less demand to C3 (Fee Structure) because they believe that the cost, while important, should not be the primary deciding factor in their pursuit of quality education. They prioritize **C2** (Scientific Research Opportunities) as they believe these will have the most significant impact on their academic and professional future.

Assume that SRNs are used to represent the evaluation values of the alternatives that correspond to each situation provided by the committee, as demonstrated in the SR-fuzzy decision matrix shown in Table 1. The component C1(S) = (0.6, 0.3) in Table 1 may have the opportunity to show that the alternative S1, SSJ Campus, the attributes C1 Academic Staff to the extent of 0.7, and the alternative S1 dissatisfies the attribute C1 to the extent of 0.3. The remaining components in Table 1 may also have those implications.

The SR-fuzzy TOPSIS approach is used in the following to solve the decision problem discussed in Sect. 9.1. First, we determine the SRPIS S+ and the FFNIS S−, respectively, using Eqs. (3) and (6). The results are as follows:

$S^+ = \{(0.6,0.3), (0.5,0.4), (0.8, 0.2), (0.3, 0.2), (0.9, 0.1)\}$

$S^- = \{(0.4, 0.5), (0.3, 0.8), (0.3, 0.6), (0.1, 0.6), (0.2, 0.4)\}$

Table 1. SR-fuzzy decision matrix.

	C1	C2	C3	C4	C5
S1	(0.6, 0.3)	(0.5, 0.4)	(0.3, 0.5)	(0.1, 0.6)	(0.3, 0.4)
S2	(0.4, 0.5)	(0.3, 0.7)	(0.2, 0.4)	(0.2, 0.3)	(0.2, 0.4)
S3	(0.6, 0.4)	(0.4, 0.5)	(0.8, 0.2)	(0.5, 0.4)	(0.4, 0.3)
S4	(0.4, 0.2)	(0.3, 0.8)	(0.3, 0.6)	(0.3, 0.2)	(0.9, 0.1)

Table 2. Score values obtained by the score function.

	C1	*C2*	*C3*	*C4*	*C5*
S1	-.188	-.382	- .617	-.764	-.542
S2	-.547	-.747	-.592	-.508	-.592
S3	-.272	-.547	.193	-.382	-.387
S4	-.287	-.804	- .684	-.357	.493

Table 3. Decision matrix SR-Fuzzy by TOPSIS.

	$D(Si , S^+)$	$D(Si , S^-)$	$\zeta(Si)$	*Ranking*
S1	0.2316	0.1213	- 0.57879	3
S2	0.3748	0.1974	- 0.93236	4
S3	0.2156	0.1949	- 0.20417	2
S4	0.2548	0.2449	- 0.18181	1

Next, by counting distances between SRPIS S+ and SRNIS S-, we independently assign Eqs. (3) and (6). Table 3 provides evidence of the consequences. Additionally, we use Eq. (9) by counting the closeness of the alternative, and the results are likewise documented in Table 3. Following this, we may obtain the placement of every option, as demonstrated in Table 3. The greatest option is S4, or DSB Campus, since Table 3 shows that the ranking order of the locations is S4 ≻ , S3≻ , S1 ≻, S2 [12. 13].

CONCLUSION

The SRFSs and SR-MGs have been started in this paper. It was demonstrated that SR-FS, Pythagorean fuzzy sets. For the case of SR-FSs, we concentrated on the basic set operations. Next, we looked at the complement of the square root fuzzy set. Given that SR-Fuzzy sets have a high ability to illustrate ambiguous evaluation data, we have examined the TOPSIS process's augmentation in SR-Fuzzy settings. Next, we presented the SR-fuzzy TOPSIS approach. An example of a typical problem in real life was used to explain the usefulness of the SR-fuzzy TOPSIS technique, and the results indicate that our method is very successful in analyzing MCDM problems with SR-fuzzy documentation. Other techniques, such as the Prioritized Aggregation Operators Garg and Nancy (2018), Robust and intelligent techniques Golshannavaz (2018), utilizing FFNs, and graph algorithms.

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