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MULTI CRITERIA DECISION MAKING UNDER SINGLE-VALUED NEUTROSOPHIC SET ENVIRONMENT FOR SUPPLIER SELECTION

(Pembuatan Keputusan Multikriteria dalam Lingkungan Himpunan Neutrosofi Bernilai Tunggal untuk Pemilihan Pembekal)

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ABSTRACT

The process of selecting suppliers is a crucial decision for organisations and has a substantial effect on enterprises, particularly in industries with extensive and constantly evolving supply chains. In this study, six predetermined criteria are used to evaluate four possible supplier choices under the proposed framework for supplier selection. These criteria include competitive pricing, distance, volume flexibility, technological capabilities, material quality, and complaint handling. This study employs the multi-criteria decision-making (MCDM) technique and single-valued neutrosophic sets (SVNS) to address the challenge of selecting a sustainable supplier with insufficient information. To achieve this, the study uses SVNS-based scoring and accuracy functions. A ranking method, specifically designed for single-valued neutrosophic numbers (SVNN), is used to effectively represent and solve the supplier selection problem. Based on the weight model, the ranking order is $A_1 > A_2 > A_4 > A_3$. Unlike other methods, this technique helps decision-makers effectively communicate imprecise and unclear information. It offers a distinct perspective and approach for MCDM in situations marked by ambiguity. In addition, it allows decision-makers select suppliers that provide exceptional quality and prioritise sustainable business practices.

Keywords: decision-making method; single-valued neutrosophic set; supplier selection

ABSTRAK

Proses memilih pembekal adalah keputusan penting bagi organisasi dan mempunyai kesan besar terhadap perniagaan, terutamanya dalam industri dengan rantaian bekalan yang luas dan sentiasa berkembang. Dalam kajian ini, enam kriteria yang telah ditetapkan digunakan untuk menilai empat pilihan pembekal di bawah kerangka kerja yang dicadangkan untuk pemilihan pembekal. Kriteria-kriteria ini termasuk harga yang kompetitif, jarak, fleksibiliti isipadu, keupayaan teknologi, kualiti bahan, dan penanganan aduan. Kajian ini menggunakan teknik pemilihan pembuat keputusan berdasarkan pelbagai kriteria (MCDM) dan set netrosofi nilai tunggal (SVNS) untuk menangani cabaran memilih pembekal yang mampan dengan maklumat yang tidak mencukupi. Untuk mencapai ini, kajian menggunakan fungsi penilaian dan ketepatan berdasarkan SVNS. Kaedah penarafan, yang direka khas untuk nombor netrosofi nilai tunggal (SVNN), digunakan untuk mewakili dan menyelesaikan masalah pemilihan pembekal dengan berkesan. Berdasarkan model berat, susunan penarafan adalah $A_1 > A_2 > A_4 > A_3$. Berbeza dengan kaedah lain, teknik ini membantu pembuat keputusan menyampaikan maklumat yang tidak tepat dan tidak jelas dengan berkesan. Ia menawarkan pandangan dan pendekatan yang berbeza untuk MCDM dalam situasi yang ditandai dengan keambiguitan. Selain itu, ia membolehkan pembuat keputusan memilih pembekal yang menyediakan kualiti yang luar biasa dan memberi keutamaan kepada amalan perniagaan mampan.

Kata kunci: kaedah membuat keputusan; set netrosofi nilai tunggal; pemilihan pembekal

1. Introduction

In the ever-changing world of supply chain management, the crucial task of choosing suppliers is frequently faced with complex obstacles. When selecting suppliers, organisations face complex criteria, uncertainty, and varying preferences. The careful selection of suppliers ensures the acquisition of top-notch goods and services at the best possible prices. This process requires a comprehensive assessment of potential suppliers, considering various factors like cost, timeliness, adaptability, innovation, quality, and service (Ghorabaee *et al.* 2016).

Supplier selection is an essential task that organisations must tackle in today's highly competitive business environment. When faced with a wide range of suppliers to consider, making a decision can be quite challenging. It is important to evaluate various criteria to make an informed choice carefully. Supplier assessment involves analysing previous performance to gain insights into reliability, quality, and timeliness (Mamavi *et al.* 2015). Having a strong financial foundation is essential for meeting commitments on time. Multi-criteria decision-making (MCDM) tackles complex decisions using methodologies such as the Analytic Hierarchy Process (AHP) and the Technique for Order of Preference by Similarity to the Ideal Solution (TOPSIS) (Bruno & Genovese 2018).

In recent years, the single-valued neutrosophic set (SVNS) theory has emerged as a powerful tool for dealing with uncertainty and imprecision in MCDM processes. Traditional decision-making approaches in supplier selection rely on crisp sets, which may not adequately capture the uncertainties and imprecisions inherent in real-world decision-making scenarios. To address this limitation, researchers have increasingly turned to using neutrosophic sets (NS) in decision-making processes. Smarandache (1998), NS framework is a powerful tool for dealing with uncertainties because it allows each element of a set to be assigned a degree of truth, falsity, or indeterminacy. This approach recognizes that decision-makers frequently operate in environments with incomplete and imprecise information.

Several studies have explored the incorporation of NS in MCDM models for supplier selection. For instance, Thao and Smarandache (2020) conducted a real-life case study to validate their proposed research on using entropy-based similarity measures of SVNS to select suppliers for a critical material used in manufacturing operations. The authors examined data from various sources and employed ESMSN and WESMSN techniques to evaluate different supplier choices. The proposed measurements showed better accuracy and consistency than the existing approaches.

Similarly, Luo *et al.* (2023) extended the VIKOR approach using SVNS to deal with the problem of selecting a sustainable supplier with limited information. In their study, the metric for SVNS distance replaced the original VIKOR method's immediate difference with the concept of "relative distance," making data processing more logical and scientific. This approach improved the quality of evaluation results by minimizing the impact of individual preferences and experiences on the final evaluation outcomes, and the issue of excessive regret caused by factor correlation. It also improved the consistency of the evaluation's outcomes.

In addition, researchers have also investigated ways to expand and adapt the current MCDM models to better suit the SVNS environment. As an example, Liu and Shi (2017) put forward an MCDM model that utilises a single-valued neutrosophic Heronian mean (SVNHM) operator to tackle the uncertainties in supplier selection. The SVNHM operator enables decision-makers to consolidate multi-criteria information while taking into account the uncertainties that arise during the decision-making process. Furthermore, the research conducted by Luo *et al.* (2023) delved into the topic of supplier selection using VIKOR with SVNS.

According to previous research, incorporating SVNS into MCDM models for supplier selection shows potential in addressing uncertainties and imprecisions in decision-making processes. The reviewed studies have shown that incorporating SVNS environments in supplier selection processes is effective. Therefore, through the incorporation of the SVNS theory, this research paper seeks to improve the decision-making process and offer valuable insights to organisations when choosing the most appropriate suppliers. An analysis of supplier selection, taken from

Ghorabaee *et al.* (2016), is utilised to assess the supplier using six criteria: competitive pricing, distance, volume flexibility, technological capabilities, material quality, and handling of complaints. There are four potential alternatives to consider when ranking the appropriate selection of a supplier: supplier 1, supplier 2, supplier 3, and supplier 4.

2. Methodology

In this section, seven steps are utilised in determining the optimal criteria for supplier selection, as proposed by Mondal and Pramanik (2014) and shown in Figure 1.

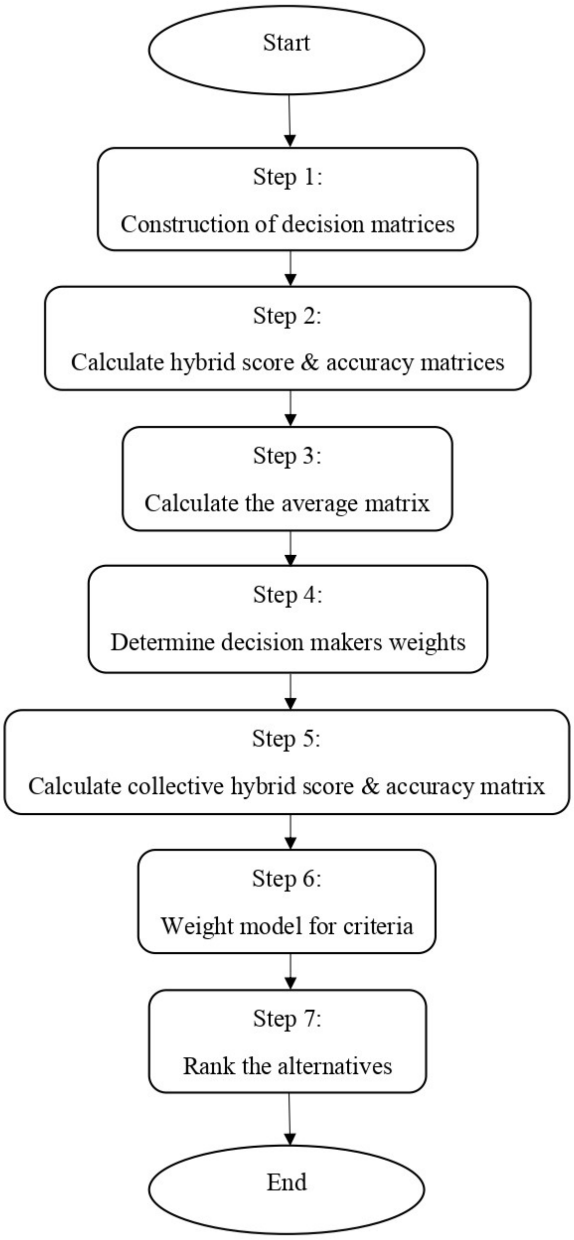

Figure 1: The flowchart of methodology

STEP 1 : Formation of the decision matrices.

In this study, the selected criteria, alternatives, and decision makers are based on existing data adapted from Ghorabaee *et al.* (2016). The criteria are competitive pricing (C_1), distance (C_2), volume flexibility (C_3), technological capabilities (C_4), material quality (C_5), and handling of complaints (C_6). While the alternatives are supplier 1 (A_1), supplier 2 (A_2), supplier 3 (A_3) and supplier 4 (A_4). Based on the data, decision matrices in the form of linguistic terms of Very Low (VL), Low (L), Medium Low (ML), Medium (M), Medium High (MH), High (H), and Very High (VH), for the decision maker 1 (DM1) until decision maker 4 (DM4) are presented in Table 1-4.

Table 1: Decision matrix for DM1 in form of linguistic term.

	C_1	C_2	C_3	C_4	C_5	C_6
A_1	H	M	M	MH	H	H
A_2	H	MH	VH	VH	H	L
A_3	L	M	H	L	L	M
A_4	M	H	M	L	ML	L

Table 2: Decision matrix for DM2 in form of linguistic term.

	C_1	C_2	C_3	C_4	C_5	C_6
A_1	MH	M	ML	M	H	H
A_2	M	M	VH	H	MH	VL
A_3	ML	ML	H	L	ML	M
A_4	M	H	M	ML	ML	L

Table 3: Decision matrix for DM3 in form of linguistic term.

	C_1	C_2	C_3	C_4	C_5	C_6
A_1	H	ML	ML	MH	MH	MH
A_2	MH	M	H	H	MH	L
A_3	ML	M	VH	ML	ML	MH
A_4	MH	MH	ML	ML	M	VL

Table 4: Decision matrix for DM4 in form of linguistic term.

	C_1	C_2	C_3	C_4	C_5	C_6
A_1	M	ML	M	M	H	MH
A_2	M	M	H	VH	H	VL
A_3	ML	ML	VH	VL	L	M
A_4	MH	MH	ML	ML	ML	VL

Karaaslan (2018) states that the linguistic term can be converted to a single-valued neutrosophic number (SVNN), which is shown in Table 5.

Table 5: Conversion between linguistic term and SVNN.

	Linguistic term	SVNN
1	Very Low(VL)	(0.05, 0.95, 0.95)
2	Low(L)	(0.20, 0.75, 0.80)
3	Medium Low(ML)	(0.35, 0.60, 0.65)
4	Medium(M)	(0.50, 0.50, 0.50)
5	Medium High(MH)	(0.65, 0.40, 0.35)
6	High(H)	(0.80, 0.25, 0.20)
7	Very High(VH)	(0.95, 0.10, 0.05)

Therefore, the decision matrices in Tables 1-4 are converted into new forms of SVNN denoted as M1, M2, M3, and M4, representing the decision matrices DM1-DM4.

$$\mathbf{M_1} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 \end{array} \\ \begin{pmatrix} (0.8,0.25,0.2) & (0.5,0.5,0.5) & (0.5,0.5,0.5) & (0.65,0.4,0.35) & (0.8,0.25,0.2) & (0.8,0.25,0.2) \\ (0.8,0.25,0.2) & (0.65,0.4,0.35) & (0.95,0.1,0.05) & (0.95,0.1,0.05) & (0.8,0.25,0.2) & (0.2,0.75,0.8) \\ (0.2,0.75,0.8) & (0.5,0.5,0.5) & (0.8,0.25,0.2) & (0.2,0.75,0.8) & (0.2,0.75,0.8) & (0.5,0.5,0.5) \\ (0.5,0.5,0.5) & (0.8,0.25,0.2) & (0.5,0.5,0.5) & (0.2,0.75,0.8) & (0.35,0.6,0.65) & (0.2,0.75,0.8) \end{pmatrix} \end{array}$$

$$\mathbf{M_2} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 \end{array} \\ \begin{pmatrix} (0.65,0.4,0.35) & (0.5,0.5,0.5) & (0.35,0.6,0.65) & (0.5,0.5,0.5) & (0.8,0.25,0.2) & (0.8,0.25,0.2) \\ (0.5,0.5,0.5) & (0.5,0.5,0.5) & (0.95,0.1,0.05) & (0.8,0.25,0.2) & (0.65,0.4,0.35) & (0.05,0.95,0.95) \\ (0.35,0.6,0.65) & (0.35,0.6,0.65) & (0.8,0.25,0.2) & (0.2,0.75,0.8) & (0.35,0.6,0.65) & (0.5,0.5,0.5) \\ (0.5,0.5,0.5) & (0.8,0.25,0.2) & (0.5,0.5,0.5) & (0.35,0.6,0.65) & (0.35,0.6,0.65) & (0.2,0.75,0.8) \end{pmatrix} \end{array}$$

$$\mathbf{M_3} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 \end{array} \\ \begin{pmatrix} (0.8,0.25,0.2) & (0.35,0.6,0.65) & (0.35,0.6,0.65) & (0.65,0.4,0.35) & (0.65,0.4,0.35) & (0.65,0.4,0.35) \\ (0.65,0.4,0.35) & (0.5,0.5,0.5) & (0.8,0.25,0.2) & (0.8,0.25,0.2) & (0.65,0.4,0.35) & (0.2,0.75,0.8) \\ (0.35,0.6,0.65) & (0.5,0.5,0.5) & (0.95,0.1,0.05) & (0.35,0.6,0.65) & (0.35,0.6,0.65) & (0.65,0.4,0.35) \\ (0.65,0.4,0.35) & (0.65,0.4,0.35) & (0.35,0.6,0.65) & (0.35,0.6,0.65) & (0.5,0.5,0.5) & (0.05,0.95,0.95) \end{pmatrix} \end{array}$$

$$\mathbf{M_4} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 \end{array} \\ \begin{pmatrix} (0.5,0.5,0.5) & (0.35,0.6,0.65) & (0.5,0.5,0.5) & (0.5,0.5,0.5) & (0.8,0.25,0.2) & (0.65,0.4,0.35) \\ (0.5,0.5,0.5) & (0.5,0.5,0.5) & (0.8,0.25,0.2) & (0.95,0.1,0.05) & (0.8,0.25,0.2) & (0.05,0.95,0.95) \\ (0.35,0.6,0.65) & (0.35,0.6,0.65) & (0.95,0.1,0.05) & (0.05,0.95,0.95) & (0.2,0.75,0.8) & (0.5,0.5,0.5) \\ (0.65,0.4,0.35) & (0.65,0.4,0.35) & (0.35,0.6,0.65) & (0.35,0.6,0.65) & (0.35,0.6,0.65) & (0.05,0.95,0.95) \end{pmatrix} \end{array}.$$

STEP 2 : Calculate the hybrid-score accuracy matrix, H

Eq. (1) calculates the hybrid score-accuracy matrix for each alternative and criterion.

$$h_{ij}^{s} = \frac{1}{2}\alpha(1 + t_{ij}^{s} - f_{ij}^{s}) + \frac{1}{3}(1 - \alpha)(2 + t_{ij}^{s} - i_{ij}^{s} - f_{ij}^{s}) \tag{1}$$

Then, the hybrid score-accuracy matrix for alternative 1 of the DM1 is calculated as below.

$$h_{11}^{1} = \frac{1}{2}(0.5)(1 + 0.8 - 0.2) + \frac{1}{3}(1 - 0.5)(2 + 0.8 - 0.25 - 0.2) = 0.7917$$

$$h_{21}^{1} = \frac{1}{2}(0.5)(1 + 0.8 - 0.2) + \frac{1}{3}(1 - 0.5)(2 + 0.8 - 0.25 - 0.2) = 0.7917.$$

Hence, all the elements in matrix H^1 of the hybrid score-accuracy matrix for DM1 is:

$$\mathbf{H^1} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 \end{array} \\ \begin{pmatrix} 0.7917 & 0.5000 & 0.5000 & 0.6417 & 0.7917 & 0.7917 \\ 0.7917 & 0.6417 & 0.9417 & 0.9417 & 0.7917 & 0.2083 \\ 0.2083 & 0.5000 & 0.7917 & 0.2083 & 0.2083 & 0.5000 \\ 0.5000 & 0.7917 & 0.5000 & 0.2083 & 0.3583 & 0.2083 \end{pmatrix} \end{array}.$$

The same step as H^1 are computed to get H^2, H^3 and H^4. Therefore, the hybrid score-accuracy matrix for DM2 until DM4 is as follows.

$$\mathbf{H^2} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 \end{array} \\ \begin{pmatrix} 0.6417 & 0.5000 & 0.3583 & 0.5000 & 0.7917 & 0.7917 \\ 0.5000 & 0.5000 & 0.9417 & 0.7917 & 0.6417 & 0.0500 \\ 0.3583 & 0.3583 & 0.7917 & 0.2083 & 0.3583 & 0.5000 \\ 0.5000 & 0.7917 & 0.5000 & 0.3583 & 0.3583 & 0.2083 \end{pmatrix} \end{array}.$$

$$\mathbf{H^3} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 \end{array} \\ \begin{pmatrix} 0.7917 & 0.3583 & 0.3583 & 0.6417 & 0.6417 & 0.6417 \\ 0.6417 & 0.5000 & 0.7917 & 0.7917 & 0.6417 & 0.2083 \\ 0.3583 & 0.5000 & 0.9417 & 0.3583 & 0.3583 & 0.6417 \\ 0.6417 & 0.6417 & 0.3583 & 0.3583 & 0.5000 & 0.0500 \end{pmatrix} \end{array}.$$

$$\mathbf{H^4} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 \end{array} \\ \begin{pmatrix} 0.5000 & 0.3583 & 0.5000 & 0.5000 & 0.7917 & 0.6417 \\ 0.5000 & 0.5000 & 0.7917 & 0.9417 & 0.7917 & 0.0500 \\ 0.3583 & 0.3583 & 0.9417 & 0.0500 & 0.2083 & 0.5000 \\ 0.6417 & 0.6417 & 0.3583 & 0.3583 & 0.3583 & 0.0500 \end{pmatrix} \end{array}.$$

STEP 3 : Calculate the average matrix H^*.

The average of the matrix is computed using Eq.(2) by combining the hybrid score-accuracy matrices for all criteria to obtain a single hybrid score-accuracy matrix for each alternative.

$$h^*_{ij} = \frac{1}{m}\sum_{s=1}^{m} h^s_{ij}. \tag{2}$$

where m is the number of decision makers and h^s_{ij} is taken from previous step.
As an example, h^*_{11} and h^*_{21} is computed as:

$$h^*_{11} = \frac{0.7917 + 0.6417 + 0.7917 + 0.5000}{4} = 0.6813$$
$$h^*_{21} = \frac{(0.7917 + 0.5000 + 0.6417 + 0.5000)}{4} = 0.6083.$$

Continue to all elements, so H^* becomes:

$$\mathbf{H}^* = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 \end{array} \\ \begin{pmatrix} 0.6813 & 0.4292 & 0.4292 & 0.5708 & 0.7542 & 0.7167 \\ 0.6083 & 0.5354 & 0.8667 & 0.8667 & 0.7167 & 0.1292 \\ 0.3208 & 0.4292 & 0.8667 & 0.2063 & 0.2833 & 0.5354 \\ 0.5708 & 0.7167 & 0.4292 & 0.3208 & 0.3938 & 0.1292 \end{pmatrix} \end{array}$$

and

$$(\mathbf{H}^*)^{\mathbf{2}} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 \end{array} \\ \begin{pmatrix} 0.4641 & 0.1842 & 0.1842 & 0.3259 & 0.5688 & 0.5136 \\ 0.3701 & 0.2867 & 0.7511 & 0.7511 & 0.5136 & 0.0167 \\ 0.1029 & 0.1842 & 0.7511 & 0.0425 & 0.0803 & 0.2867 \\ 0.3259 & 0.5136 & 0.1842 & 0.1029 & 0.1550 & 0.0167 \end{pmatrix} \end{array}.$$

Then,

$$(\mathbf{H}^{\mathbf{1}})(\mathbf{H}^*) = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 \end{array} \\ \begin{pmatrix} 0.5393 & 0.2146 & 0.2146 & 0.3663 & 0.5970 & 0.5674 \\ 0.4816 & 0.3436 & 0.8161 & 0.8161 & 0.5674 & 0.0269 \\ 0.0668 & 0.2146 & 0.6861 & 0.0430 & 0.0590 & 0.2677 \\ 0.2854 & 0.5674 & 0.2146 & 0.0668 & 0.1411 & 0.0269 \end{pmatrix} \end{array}$$

and

$$(\mathbf{H}^{\mathbf{1}})^{\mathbf{2}} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 \end{array} \\ \begin{pmatrix} 0.6267 & 0.2500 & 0.2500 & 0.4117 & 0.6267 & 0.6267 \\ 0.6267 & 0.4117 & 0.8867 & 0.8667 & 0.6267 & 0.0434 \\ 0.0434 & 0.2500 & 0.6267 & 0.0434 & 0.0434 & 0.2500 \\ 0.2500 & 0.6267 & 0.2500 & 0.0434 & 0.1284 & 0.0434 \end{pmatrix} \end{array}.$$

Next, the collective correlation coefficient of H^1 is determined step by step using Eq. (3) for each alternative.

$$\Omega_s = \sum_{i=1}^{n} \frac{\sum_{j=1}^{\rho} h_{ij}^s h_{ij}^*}{\sqrt{\sum_{j=1}^{\rho}(h_{ij}^s)^2}\sqrt{\sum_{j=1}^{\rho}(h_{ij}^*)^2}} \tag{3}$$

So, for alternative 1, it computed as

$$\begin{aligned}
\sum_{j=1}^{\rho} h_{1j}^1 h_{1j}^* &= (0.5393 + 0.2146 + 0.2146 + 0.3663 + 0.5970 + 0.5674) = 2.4992 \\
\sqrt{\sum_{j=1}^{\rho} (h_{1j}^1)^2} &= \sqrt{(0.6267 + 0.2500 + 0.2500 + 0.4117 + 0.6267 + 0.6267)} = 1.6709 \\
\sqrt{\sum_{j=1}^{\rho} (h_{1j}^*)^2} &= \sqrt{(0.4641 + 0.1842 + 0.1842 + 0.3259 + 0.5688 + 0.5136)} = 1.4969
\end{aligned}$$

then from Eq. (3),

$$\frac{\sum_{j=1}^{\rho} h_{1j}^1 h_{1j}^*}{\sqrt{\sum_{j=1}^{\rho} (h_{1j}^1)^2}\sqrt{\sum_{j=1}^{\rho} (h_{1j}^*)^2}} = \frac{2.4992}{(1.6709)(1.4969)} = 0.9992.$$

Alternative 2, 3 and 4 are calculated using similar steps.

$$\frac{\sum_{j=1}^{\rho} h_{2j}^1 h_{2j}^*}{\sqrt{\sum_{j=1}^{\rho} (h_{2j}^1)^2}\sqrt{\sum_{j=1}^{\rho} (h_{2j}^*)^2}} = \frac{3.0516}{(1.8660)(1.6399)} = 0.9972.$$

$$\frac{\sum_{j=1}^{\rho} h_{3j}^1 h_{3j}^*}{\sqrt{\sum_{j=1}^{\rho} (h_{3j}^1)^2}\sqrt{\sum_{j=1}^{\rho} (h_{3j}^*)^2}} = \frac{1.3372}{(1.1211)(1.2032)} = 0.9913.$$

$$\frac{\sum_{j=1}^{\rho} h_{4j}^1 h_{4j}^*}{\sqrt{\sum_{j=1}^{\rho} (h_{4j}^1)^2}\sqrt{\sum_{j=1}^{\rho} (h_{4j}^*)^2}} = \frac{1.3022}{(1.1584)(1.1394)} = 0.9866.$$

Hence, the collective correlation co-efficient of H^1 become:

$$\Omega_1 = 0.9992 + 0.9972 + 0.9913 + 0.9866 = 3.9743.$$

while for H^2, H^3, H^4 respectively computed as

$$\begin{aligned}
\Omega_2 &= 0.9949 + 0.9942 + 0.9945 + 0.9921 = 3.9756 \\
\Omega_3 &= 0.9899 + 0.9969 + 0.9949 + 0.9869 = 3.9687 \\
\Omega_4 &= 0.9898 + 0.9933 + 0.9850 + 0.9908 = 3.9588.
\end{aligned}$$

Hence, the cumulative co-efficient of H^1, H^2, H^3 and H^4 is

$$\sum_{s=1}^{m} \Omega_s = 3.9743 + 3.9756 + 3.9687 + 3.9588 = 15.8775.$$

STEP 4 : Determine the weights of the decision-makers.

The weight of the decision maker is determined by Eq. (4) as

$$\gamma_s = \frac{\Omega_s}{\sum_{s=1}^{m} \Omega_s}, 0 \leq \gamma_s \leq 1, \sum_{s=1}^{m} \gamma_s = 1 \text{ for } s = 1, 2, \ldots, m. \tag{4}$$

So, the weight for each decision maker in this study becomes,

$$\begin{aligned}
\gamma_1 &= \frac{\Omega_1}{\sum_{s=1}^{m} \Omega_s} = \frac{3.9743}{15.8775} = 0.2503 \\
\gamma_2 &= \frac{\Omega_2}{\sum_{s=1}^{m} \Omega_s} = \frac{3.9756}{15.8775} = 0.2504 \\
\gamma_3 &= \frac{\Omega_3}{\sum_{s=1}^{m} \Omega_s} = \frac{3.9687}{15.8775} = 0.2500 \\
\gamma_4 &= \frac{\Omega_4}{\sum_{s=1}^{m} \Omega_s} = \frac{3.9588}{15.8775} = 0.2493.
\end{aligned}$$

The weight values obtained above represent their relative importance in making such a decision.

STEP 5 : Calculate the collective hybrid score-accuracy matrix.

The collective hybrid score-accuracy matrix is determined by using Eq. (5) where the equation is a combination of input from each decision maker in Step 2 with the corresponding weight from the decision maker in Step 4.

$$h_{ij} = \sum_{s=1}^{m} \gamma_s \, h_{ij}^{s}. \tag{5}$$

By that,

$$\begin{aligned}
h_{1(11)} &= 0.2503 \times 0.7917 = 0.1982 \\
h_{1(12)} &= 0.2503 \times 0.5000 = 0.1252
\end{aligned}$$

and others element are computed same as above to have $[\mathbf{H^1}]\boldsymbol{\gamma_1}$ as below.

$$[\mathbf{H^1}]\boldsymbol{\gamma_1} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 \end{array} \\ \begin{pmatrix} 0.1982 & 0.1252 & 0.1252 & 0.1606 & 0.1982 & 0.1982 \\ 0.1982 & 0.1606 & 0.2357 & 0.2357 & 0.1982 & 0.0521 \\ 0.0521 & 0.1252 & 0.1982 & 0.0521 & 0.0521 & 0.1252 \\ 0.1252 & 0.1982 & 0.1252 & 0.0521 & 0.0897 & 0.0521 \end{pmatrix} \end{array}$$

Then, the same calculation are computed to obtain $[\mathbf{H^2}]\boldsymbol{\gamma_2}$, $[\mathbf{H^3}]\boldsymbol{\gamma_3}$ and $[\mathbf{H^4}]\boldsymbol{\gamma_4}$. Alternative 2 is calculated as follows:

$$\begin{aligned}
h_{2(11)} &= 0.2504 \times 0.6417 = 0.1607 \\
h_{2(12)} &= 0.2504 \times 0.5000 = 0.1252
\end{aligned}$$

and,

$$[\mathbf{H^2}]\gamma_{\mathbf{2}} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 \end{array} \\ \begin{pmatrix} 0.1607 & 0.1252 & 0.0897 & 0.1252 & 0.1982 & 0.1982 \\ 0.1252 & 0.1252 & 0.2358 & 0.1982 & 0.1607 & 0.0125 \\ 0.0897 & 0.0897 & 0.1982 & 0.0522 & 0.0897 & 0.1252 \\ 0.1252 & 0.1982 & 0.1252 & 0.0897 & 0.0897 & 0.0522 \end{pmatrix} \end{array}.$$

For alternative 3, the computation is

$$h_{3(11)} = 0.7917 \times 0.2500 = 0.1979$$
$$h_{3(12)} = 0.3583 \times 0.2500 = 0.0896$$

to have

$$[\mathbf{H^3}]\gamma_{\mathbf{3}} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 \end{array} \\ \begin{pmatrix} 0.1979 & 0.0896 & 0.0896 & 0.1604 & 0.1604 & 0.1604 \\ 0.1604 & 0.1250 & 0.1979 & 0.1979 & 0.1604 & 0.0521 \\ 0.0896 & 0.1250 & 0.2354 & 0.0896 & 0.0896 & 0.1604 \\ 0.1604 & 0.1604 & 0.0896 & 0.0896 & 0.1250 & 0.0125 \end{pmatrix} \end{array}$$

and lastly alternative 4 is computed as:

$$h_{4(11)} = 0.5000 \times 0.2493 = 0.1247 h_{4(12)} = 0.3583 \times 0.2493 = 0.0893$$

gives

$$[\mathbf{H^4}]\gamma_{\mathbf{4}} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 \end{array} \\ \begin{pmatrix} 0.1247 & 0.0893 & 0.1247 & 0.1247 & 0.1974 & 0.1600 \\ 0.1247 & 0.1247 & 0.1974 & 0.2348 & 0.1974 & 0.0125 \\ 0.0893 & 0.0893 & 0.2348 & 0.0125 & 0.0519 & 0.1247 \\ 0.1600 & 0.1600 & 0.0893 & 0.0893 & 0.0893 & 0.0125 \end{pmatrix} \end{array}.$$

By that, the collective hybrid score-accuracy matrix, *H*, is easily computed by totaling up each element in each row for all decision makers. Hence,

$$\begin{aligned} h_{11} &= h_{1(11)} + h_{2(11)} + h_{3(11)} + h_{4(11)} \\ &= 0.1982 + 0.1607 + 0.1979 + 0.1247 = 0.6814 \\ h_{21} &= h_{1(21)} + h_{2(21)} + h_{3(21)} + h_{4(12)} \\ &= 0.1982 + 0.1252 + 0.1604 + 0.1247 = 0.6084 \\ h_{31} &= h_{1(31)} + h_{2(31)} + h_{3(31)} + h_{4(32)} \\ &= 0.0521 + 0.0897 + 0.0896 + 0.0893 = 0.3208 \\ h_{41} &= h_{1(41)} + h_{2(41)} + h_{3(41)} + h_{4(42)} \\ &= 0.1252 + 0.1252 + 0.1604 + 0.1600 = 0.5707. \end{aligned}$$

To completely have the collective hybrid score-accuracy matrix, *H* below, repeats the same calculation for other elements.

$$\mathbf{H} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 \end{array} \\ \begin{pmatrix} 0.6814 & 0.4293 & 0.1247 & 0.5709 & 0.7542 & 0.7168 \\ 0.6084 & 0.5355 & 0.8668 & 0.8666 & 0.7166 & 0.1292 \\ 0.3208 & 0.4292 & 0.8668 & 0.2063 & 0.2834 & 0.5354 \\ 0.5707 & 0.7168 & 0.4293 & 0.3208 & 0.3937 & 0.1293 \end{pmatrix} \end{array}.$$

STEP 6 : Weight model for criteria.

It is worth noting that the weight vector or weight model can be determined by the algorithm introduced by Ye (2014). In this study, weight vectors from Abdel-Basset *et al.* (2019) : $\omega_B = (0.1, 0.2, 0.1, 0.1, 0.3, 0.2)^T$, is used.

STEP 7: Ranking of alternatives.

Equation (6) is used to rank the alternative, which is the final step.

$$\Psi(A_i) = \sum_{j=1}^{\rho} \omega_i h_{ij}. \tag{6}$$

Weights for each alternative are calculated using Eq. (6) by multiplying the values in the decision matrix, *H*, in Step 5 by the corresponding weight model values in Step 6. The $\omega_B(H)$ for criteria 1 is calculated as follows:

$$\begin{aligned} \omega_1 h_{11} &= 0.1 \times 0.6814 = 0.0681 \\ \omega_1 h_{21} &= 0.1 \times 0.6084 = 0.0608 \\ \omega_1 h_{31} &= 0.1 \times 0.3208 = 0.0321 \\ \omega_1 h_{41} &= 0.1 \times 0.5707 = 0.0571 \end{aligned}$$

Therefore, $\omega_B(H)$ become:

$$\omega_{\mathbf{B}}(\mathbf{H}) = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 \end{array} \\ \begin{pmatrix} 0.0681 & 0.0859 & 0.0429 & 0.0571 & 0.2263 & 0.1434 \\ 0.0608 & 0.1071 & 0.0867 & 0.0867 & 0.2150 & 0.0258 \\ 0.0321 & 0.0858 & 0.0867 & 0.0206 & 0.0850 & 0.1071 \\ 0.0571 & 0.1434 & 0.0429 & 0.0321 & 0.1181 & 0.0259 \end{pmatrix} \end{array}.$$

Hence, the total sum of

$$\begin{aligned}\Psi(A_1) &= \omega_1 h_{11} + \omega_2 h_{12} + \omega_3 h_{13} + \omega_4 h_{14} + \omega_5 h_{15} + \omega_6 h_{16} \\ &= 0.0681 + 0.0859 + 0.0429 + 0.0571 + 0.2263 + 0.1434 = 0.6236\end{aligned}$$

$$\begin{aligned}\Psi(A_2) &= \omega_1 h_{21} + \omega_2 h_{22} + \omega_3 h_{23} + \omega_4 h_{24} + \omega_5 h_{25} + \omega_6 h_{26} \\ &= 0.0608 + 0.1071 + 0.0867 + 0.0867 + 0.2150 + 0.0258 = 0.5821\end{aligned}$$

$$\begin{aligned}\Psi(A_3) &= \omega_1 h_{31} + \omega_2 h_{32} + \omega_3 h_{33} + \omega_4 h_{34} + \omega_5 h_{35} + \omega_6 h_{36} \\ &= 0.0321 + 0.0858 + 0.0867 + 0.0206 + 0.0850 + 0.1071 = 0.4173\end{aligned}$$

and

$$\begin{aligned}\Psi(A_4) &= \omega_1 h_{41} + \omega_2 h_{42} + \omega_3 h_{43} + \omega_4 h_{44} + \omega_5 h_{45} + \omega_6 h_{46} \\ &= 0.0571 + 0.1434 + 0.0429 + 0.0321 + 0.1181 + 0.0259 = 0.4195\end{aligned}$$

According to the above values, the highest value is the most preferred ranking. Hence, the rank of the best supplier in descending order is $\Psi(A_1) > \Psi(A_2) > \Psi(A_4) > \Psi(A_3)$.

3. Results

This study focuses on the proposed decision-making method using SVNS to rank supplier selection. The SVNS provides a comprehensive framework for evaluating and ranking suppliers based on a variety of criteria, taking into account the uncertainties and imprecisions inherent in the decision-making process.

The existing data from Ghorabaee *et al.* (2016) for supplier selection is taken into account using the SVNS approach. The dataset includes a variety of criteria, including competitive pricing, distance, volume flexibility, and technological capabilities. SVNS is used to represent the linguistic term specified by decision-makers.

The outcome of the supplier selection process, as evaluated by Ghorabaee *et al.* (2016), was compared with the existing data. From Ghorabaee *et al.* (2016) weight model, the ranking order of alternatives is $A_1 > A_2 > A_4 > A_3$. These rankings indicate that the preferences and priorities chosen for the alternatives slightly differ depending on the weight model used.

Table 6: The results with weight models and from existing findings.

Weight Models	Result obtained	Fuzzy DEMATEL ranking by Ghorabaee *et al.* (2016)
$\omega_B = (0.1, 0.2, 0.1, 0.1, 0.3, 0.2)^T$	$A_1 > A_2 > A_4 > A_3$	$A_1 > A_2 > A_4 > A_3$

Based on the results, the weight model determines that A_1 is the most favorable option. This suggests that the weight model places greater importance on the attributes or criteria associated with A_1. As part of a comparison, the obtained results are being compared to the results from a previous study conducted by Ghorabaee *et al.* (2016) using fuzzy DEMATEL. Based on their study, the result shows that A_1 is the top-ranked alternative. In comparison to these results, it is evident that the weight model proposed by Abdel-Basset *et al.* (2019) has successfully achieved equal rankings.

The result obtained from this study demonstrates a similarity when compared to fuzzy DEMATEL. To summarise, the study's weight model and fuzzy DEMATEL show similar results, despite differences in data calculation environments. This indicates the effectiveness and robustness of the study's model. However, it is important to carefully consider contextual and data-related factors in order to conduct a thorough evaluation of this similarity.

4. Conclusion

This research focused on applying the SVNS decision-making approach to the supplier selection process in an MCDM context. The SVNS MCDM framework was used to evaluate and rank suppliers, considering the inherent uncertainties and imprecision of decision-making. The SVNS MCDM method was used to pursue a holistic and comprehensive approach to supplier evaluation and rating, considering the complexities and uncertainties prevalent in the decision-making process. In addition, the study's objectives have been successfully achieved. First, we conducted a case study on supplier selection in the SVNS environment, using a decision-making process. Additionally, the study effectively determined and prioritised the primary options that impacted the selection of suppliers by consumers.

Additionally, this study highlights the superior effectiveness of SVNS MCDM in decision-making processes. By implementing a three-level accuracy system in SVNS MCDM, decision-makers are able to effectively handle fuzzy lack of information data. This system includes truth, indeterminacy, and falsehood, allowing for better management of the data. Based on the findings and conclusions of this research, there are several recommendations that can be made. First and foremost, decision-makers should meticulously choose a weight model that aligns with their supplier selection preferences and objectives. This ensures that the rankings accurately represent their goals. Furthermore, it would be beneficial for future studies to explore the impact of various weight models on decision outcomes. Conducting comparative research with larger sample sizes and across industries could offer valuable insights into the reliability and adaptability of these models. Additionally, in future research, it would be beneficial to conduct a comparative study with other methods in SVNS of MCDM, such as single value neutrosopic Heronian mean (SVNHM) and VIKOR with SVNS.

It is necessary to consistently monitor and review the performance of suppliers. Regular assessments and stakeholder feedback help to identify changes in the decision context, enabling adjustments in weight models and decision-making techniques. Following these recommendations improves the effectiveness of supplier selection, which leads to improved organisational performance.

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