A Multi-Attribute Group Decision-Making Approach Based on Entropy of Single-Valued Neutrosophic Set for TOPSIS

Dongsheng Xu, Yuanyuan Peng, Lijuan Hu, Lin Jiang

Abstract—**This study addresses the challenges of multi-attribute group decision-making (MAGDM) under uncertainty by proposing a dual-innovation framework that leverages single-valued neutrosophic set (SVNS) to improve decision-making processes. Traditional methods face two major limitations: (1) static weight vectors that fail to capture the dynamic preference structures of decision-makers (DMs) across attributes and alternatives, and (2) aggregation operators that are weight-dependent and computationally complex. To overcome these problems, we introduce a novel entropy-driven two-dimensional weight matrix to dynamically capture variations in attribute preferences across alternatives, thus replacing the rigidity of fixed-weight models. Additionally, we develop a truncated mean aggregation approach that eliminates the need for precise weight assignment by adaptively filtering out extreme evaluations, creating a robust decision-making paradigm that is resistant to outliers. These innovations are integrated into the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) framework and validated through a case study, demonstrating improved alignment with DMs' preferences. Furthermore, the framework's compatibility with other neutrosophic measures makes it a versatile tool for complex decision-making applications in the future.**

Index Terms—**MAGDM, Entropy, SVNS, Truncated mean approach, TOPSIS**

I. Introduction

ACCURATE preference representation and efficient information processing remain fundamental challenges in multi-attribute decision-making (MADM), particularly in uncertain environments. Zadeh's fuzzy set (FS) [1] was the first to quantify uncertainty through membership functions $\mu_A(x)$, which sparked the development of subsequent extensions [2]–[5]. However, these extensions do not address all types of uncertainty encountered in real-world applications. For example, a statement may have a truth degree of 0.5, an uncertainty degree of 0.2, and a falsity degree of 0.6. To overcome this, Smarandache's neutrosophic set (NS) [6] introduced independent membership functions for truth (T), indeterminacy (I), and falsity (F). While this framework possesses theoretical strengths, it was initially constrained by using non-standard intervals $]0^-, 1^+[$. Wang et al. [7] addressed this by introducing the single-valued neutrosophic set (SVNS), where $T, I, F \in [0,1]$, ensuring both mathematical rigor and operational feasibility. Since then, SVNS has significantly advanced MADM by allowing for independent handling of uncertainty. Traditional decision-making methods such as TODIM [8], TOPSIS [9], VIKOR [10], and ELECTRE [11] have been adapted to work within SVNS environments, improving conflict resolution and managing incomplete data [12]–[14]. Furthermore, tools like distance metrics [15], [16], similarity indices [17], [18], score functions [19], [20], correlation coefficients [21], entropy measures [22], [23], and aggregation operators [24], [25] have contributed to creating a robust framework for SVNS-based decision analysis. Despite these advancements, two ongoing challenges—weight determination and aggregation mechanisms—still impede the broader application of SVNS.

Weight allocation is critical for prioritizing criteria in MADM. Xu et al. [26] proposed a deviation maximization-based weight model, later extended by Maghrabie et al. [27] through grey system theory to account for deviation and correlation effects. Ji et al. [28] applied a mean square deviation-weighting method to assign weights to selected criteria. Garg [29] introduced a new entropy index measure for weight extraction and information aggregation. Mishra et al. [30] developed a novel score function and divergence measure to determine expert and attribute weights. Wang [31] proposed a normalized score function within the SVNS framework to derive attribute weights. Additionally, weight models have been widely applied to integrate and optimize traditional MADM methods. For instance, Tian et al. [32] combined SVNS with flexible multi-criteria methods to handle cases with unknown criterion weights. Kara et al. [33] proposed an SVNS-CRITIC-TOPSIS model for software selection, using linguistic SVNS to capture expert expressions. Zhang et al. [34] enhanced cumulative prospect theory by integrating it with binary linguistic sets and applied the entropy weight method to the Evaluation based on Distance from Average Solution (EDAS) method. Thong et al. [35] developed an optimization framework to determine attribute weights and introduced an innovative TOPSIS method. Finally, Xu et al. [36] established nonlinear constraint optimization rules based on the Best-Worst method to determine the weights and select options for different criteria.

Aggregation operators in MADM are intrinsically tied to weight parameters, which dictate information aggregation.

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The interdependence between weights and operators has led to extensive research in operator development. Ye [24] pioneered the single-valued neutrosophic weighted averaging (SVNWA) and geometric (SVNWG) operators, embedding weight vectors directly into their formulations. Subsequent advancements include triangular weighted average and geometric operators [37]. More recent innovations focus on dynamic weight integration within operator frameworks. For example, Li et al. [38] developed Dombi operations with a parameter, enabling dynamic weight assignment to input values. Farid et al. [39] proposed a multi-attribute group decision-making (MAGDM) algorithm based on the single-valued Einstein priority operator, which encodes weight dependencies through nested parametric structures. Similarly, Goyal [40] combined this operator with a weighted standard deviation model, while Singh et al. [41] established a generalized divergence measure rooted in common aggregation principles. Although each operator family embodies distinct weight integration philosophies, they all incorporate weight parameters into their computational logic. These advancements highlight a paradigm shift toward operator-weight synergy, enabling systematic trade-offs between conflicting criteria. Collectively, these innovations enhance the precision and adaptability of MADM systems.

This paper reviews recent advancements in SVNS environments, focusing on weight determination and aggregation algorithms. A key limitation of existing SVNS weighting methods lies in their compression of multidimensional preferences into a fixed vector $W = (w_1, w_2, \ldots, w_n)$, overlooking the dynamic prioritization of attributes by decision-makers (DMs) across alternatives. For example, entropy-based methods [34] and optimization-oriented approaches [35], [36] quantify decision uncertainty but assume fixed attribute weights (e.g., w_j = 0.3 for all alternatives). Similarly, divergence-driven techniques [41] assign weights by measuring inter-attribute differences, yet they lack adaptability in complex scenarios. In practice, attribute weights should vary across alternatives, reflecting evolving decision contexts and DMs' changing preferences. Moreover, when these weights are applied to aggregation operators, they face inherent constraints as they rely heavily on precise parameterization. This limitation restricts their applicability in real-world situations where weights may be ambiguous, only partially known, or subject to change. Additionally, existing operators [37]–[39] further complicate these difficulties due to their computational complexity and instability under weight uncertainty. These challenges underscore the need for more flexible weight determination strategies and efficient information aggregation techniques in SVNS-based decision-making. This study addresses existing gaps by proposing a novel method for weight determination and information aggregation in SVNS-based MAGDM.

The key contributions are as follows:

- A method for constructing a two-dimensional weight matrix based on SVNS entropy is introduced. This method captures the dynamic preferences of DMs for attributes across various alternatives, overcoming the limitations of fixed-weight vectors.
- A simplified truncated mean SVNS aggregation approach is presented. This approach is practical and does not require precise weight determination, thus expanding the range of applicable aggregation algorithms.
- The proposed method is integrated into the TOPSIS framework of SVNS, and its effectiveness is demonstrated through a case study.

The organization of this paper is as follows. Section 2 reviews simplified neutrosophic sets (SNS) and SVNS. Section 3 revisits the traditional TOPSIS method. Section 4 details the methodological innovations. Section 5 constructs an SVNS-based MAGDM framework and demonstrates its applicability through a numerical case study. Section 6 offers a comparative analysis, and Section 7 concludes with contributions and future research directions. Fig. 1 provides a visual representation of the research framework to enhance clarity.

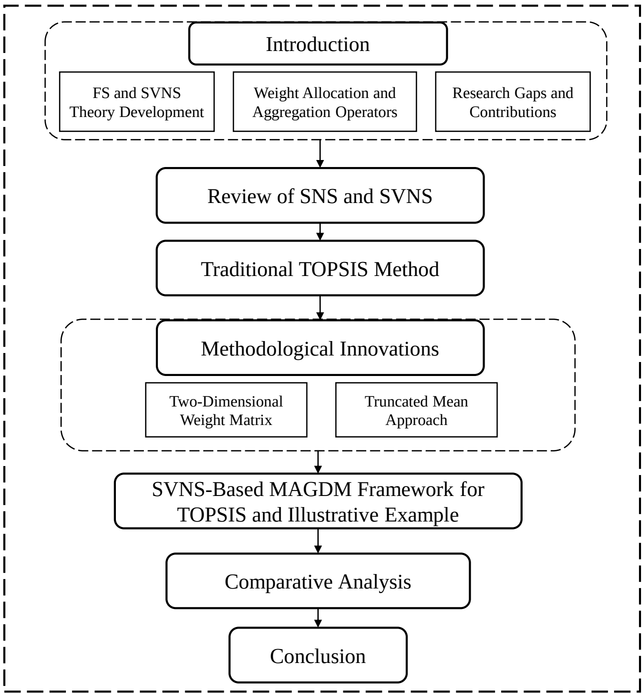

Fig. 1. Research framework

II. Preliminaries

This section defines SNS and SVNS, explains their operational mechanisms, and introduces comparative analysis methods, laying the groundwork for subsequent discussions.

A. SNS

Definition 1 [24]. Let X be a set of points (objects), with each element denoted by x. A simplified neutrosophic set A is defined as:

$$A = \{\langle x, T_A(x), I_A(x), F_A(x)\rangle \mid x \in X\} \quad (1)$$

The set A consists of three membership functions: $T_A(x)$, $I_A(x)$ and $F_A(x)$, which represent the degrees of truth, uncertainty, and falsity, respectively. These functions are defined on singleton subintervals within $[0, 1]$, and the sum of their supremums satisfies the condition: $0 \leq \sup(T_A(x)) + \sup(I_A(x)) + \sup(F_A(x)) \leq 3$. When A contains a single element, it is referred to as a simplified neutrosophic number (SNN), denoted by $A = \langle T_A, I_A, F_A \rangle$.

Definition 2 [42]. Let $A = \langle T_A, I_A, F_A \rangle$ and $B = \langle T_B, I_B, F_B \rangle$ represent two SNNs, with $\lambda > 0$. The operations on SNNs are given by the equations below:

1) $A \otimes B = \langle T_A T_B, I_A + I_B - I_A I_B, F_A + F_B - F_A F_B \rangle$.
2) $A \oplus B = \langle T_A + T_B - T_A T_B, I_A I_B, F_A F_B \rangle$.
3) $A^\lambda = \langle (T_A)^\lambda, 1 - (1 - I_A)^\lambda, 1 - (1 - F_A)^\lambda \rangle$.
4) $\lambda A = \langle 1 - (1 - T_A)^\lambda, (I_A)^\lambda, (F_A)^\lambda \rangle$.

Definition 3 [42]. Let $A_j = \langle T_{A_j}, I_{A_j}, F_{A_j} \rangle$, $(j = 1, \ldots, n)$ represent a set of SNNs. The SNNWA and SNNWG operators are defined as follows:

$$SNNWA_w(A_1, A_2, \ldots, A_n) = \sum_{j=1}^{n} \omega_j A_j$$
$$= \langle 1 - \prod_{j=1}^{n} (1 - T_{A_j})^{\omega_j}, \prod_{j=1}^{n} (I_{A_j})^{\omega_j}, \prod_{j=1}^{n} (F_{A_j})^{\omega_j} \rangle \quad (2)$$

$$SNNWG_w(A_1, A_2, \ldots, A_n) = \sum_{j=1}^{n} \omega_j A_j$$
$$= \langle \prod_{j=1}^{n} (T_{A_j})^{\omega_j}, 1 - \prod_{j=1}^{n} (1 - I_{A_j})^{\omega_j}, 1 - \prod_{j=1}^{n} (1 - F_{A_j})^{\omega_j} \rangle \quad (3)$$

Where $\omega = (\omega_1, \omega_2, \ldots, \omega_n)$ is the weight vector of A_j, satisfying $\omega_j \geq 0$ and $\sum_{j=1}^{n} \omega_j = 1$.

Definition 4 [42]. Let $A = \langle T_A, I_A, F_A \rangle$ be an SNN. The score function $s(A)$, accuracy function $a(A)$, and certainty function $c(A)$ of the SNN are defined as follows:

$$s(A) = \frac{1}{3}(2 + T_A - I_A - F_A) \quad (4)$$

$$a(A) = T_A - F_A \quad (5)$$

$$c(A) = T_A \quad (6)$$

The score function assesses the relative merit of an element by considering the combined effects of truth, falsity, and indeterminacy. For a given SNN A, a higher score T_A corresponds to a greater SNN, whereas lower values of I_A and F_A also indicate a greater SNN. The accuracy function suggests that a more affirmative statement reflects a greater contrast between truth and falsity. Similarly, the certainty function indicates that the certainty of an SNN is positively correlated with T_A.

Definition 5 [42]. Let A and B be two SNNs. The comparison rules for these SNNs are as follows:

1) If $s(A) > s(B)$, then A is considered superior to B, represented as $A > B$.
2) If $s(A) = s(B)$ and $a(A) > a(B)$, then A is also superior to B, expressed as $A > B$.
3) If $s(A) = s(B)$, $a(A) = a(B)$, and $c(A) > c(B)$, then A is superior to B, represented as $A > B$.
4) If $s(A) = s(B)$, $a(A) = a(B)$, and $c(A) = c(B)$, then A is indifferent to B, indicated by $A \sim B$.

B. SVNS

Definition 6 [7]. Let $X = \{x_1, \ldots, x_n\}$ be a space of points (objects), where each $x_i \in X$ represents an individual point. The SVNS A is then expressed as:

$$A = \sum_{i=1}^{n} \frac{\langle T_A(x_i), I_A(x_i), F_A(x_i) \rangle}{x_i}, \, x_i \in X \quad (7)$$

For an SVNS A, $T_A(x), I_A(x), F_A(x) \in [0, 1]$, and the triplet $\{\langle T_A(x), I_A(x), F_A(x) \rangle\}$ is called single-valued neutrosophic number (SVNN). To simplify, we can denote the SVNS concisely as $A = \langle T_A, I_A, F_A \rangle$. From this, it is clear that the operations and comparison methods developed for SNNs are directly applicable to SVNNs.

Definition 7 [7]. For all x in X, the concepts of containment, complement, union, and intersection for SVNSs A and B are defined as follows:

1) $A \subseteq B$, if $T_A(x) \leq T_B(x)$, $I_A(x) \leq I_B(x)$, $F_A(x) \leq F_B(x)$.
2) $A = B$, if $A \subseteq B$ and $B \subseteq A$.
3) $A^C = \{\langle T_A(x), \, 1 - I_A(x), \, F_A(x) \rangle\}$.
4) $A \cup B = \{\max(T_A(x), T_B(x)), \max(I_A(x), I_B(x)), \min(F_A(x), F_B(x))\}$.
5) $A \cap B = \{\min(T_A(x), T_B(x)), \min(I_A(x), I_B(x)), \max(F_A(x), F_B(x))\}$.

Definition 8 [43]. Entropy measure E_1 of SVNS A is computed as follows:

$$E_1(A) = 1 - \frac{1}{n} \sum_{x_i \in X} (T_A(x_i) + F_A(x_i)) \cdot |I_A(x_i) - I_{A^c}(x_i)| \quad (8)$$

Definition 9 [43]. The Euclidean distance D_1 and normalized Euclidean distance D_2 between SVNSs A and B are formulated as follows:

$$D_1(A, B) = \sum_{i=1}^{n} \Big((T_A(x_i) - T_B(x_i))^2 + (I_A(x_i) - I_B(x_i))^2 + (F_A(x_i) - F_B(x_i))^2 \Big)^{1/2} \quad (9)$$

$$D_2(A, B) = \frac{1}{3n} \sum_{i=1}^{n} \Big((T_A(x_i) - T_B(x_i))^2 + (I_A(x_i) - I_B(x_i))^2 + (F_A(x_i) - F_B(x_i))^2 \Big)^{1/2} \quad (10)$$

III. TOPSIS Method

The TOPSIS method [44] evaluates and ranks alternatives by calculating their relative distances from the Positive Ideal Solution (PIS) and the Negative Ideal Solution (NIS). The primary steps involved are: constructing a standardized decision matrix, determining attribute weights, computing the distances between each alternative and the PIS and NIS, and finally, generating a global ranking based on the relative closeness index. The necessary steps of the traditional TOPSIS method are outlined below:

Step 1: Construct the standardized decision matrix.

$$R_{ij} = \frac{r_{ij}}{\sqrt{\sum_{i=1}^{n} r_{ij}^2}}, i = 1, \ldots, m; j = 1, \ldots, n \quad (11)$$

Where r_{ij} denotes the raw value of the j^{th} attribute corresponding to the i^{th} alternative.

Step 2: Construct the weighted standardized decision matrix.

$$Z_{ij} = w_j r_{ij} \tag{12}$$

Where w_j represents the weight of the j^{th} attribute.

Step 3: Determine the PIS, A^+ and NIS, A^-.

$$A^+ = (z_1^+, \ldots, z_n^+) \tag{13}$$

$$A^+ = (z_1^-, \ldots, z_n^-) \tag{14}$$

Where $z_j^+ = \{\max_i z_{ij}\} \mid j \in J\}$, $z_j^- = \{\min_i z_{ij} \mid j \in J\}$, $i = 1, \ldots, m$.

Step 4: Compute the distance D_i^+ and D_i^-.

$$D_i^+ = \sqrt{\sum_{j=1}^{n} (z_{ij} - z_j^+)^2} \tag{15}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} (z_{ij} - z_j^-)^2} \tag{16}$$

Where D_i^+ denotes the shortest distance to the PIS, and D_i^- represents the greatest distance to the NIS.

Step 5: Calculate the relative closeness S_i.

$$S_i = \frac{D_i^-}{D_i^+ + D_i^-}, \quad S_i \in [0, 1] \tag{17}$$

The S_i quantifies the degree of superiority of each alternative. A higher relative closeness value indicates a more favorable evaluation, while a lower value suggests a less favorable one. Consequently, the alternative with the highest relative closeness is considered optimal, while the one with the lowest relative closeness is deemed the least favorable.

IV. Dual Innovations: Entropy-Based Weight Determination and Truncated Mean Aggregation

A. Problem Overview

Assume that $A = \{A_1, \ldots, A_m\}$ and $B = \{B_1, \ldots, B_n\}$ represent m alternatives and n attributes, respectively. Let X be an SVNS, where $a_{ij} = (T_{ij}, I_{ij}, F_{ij})$ denotes the SVNN corresponding to the evaluation of the j^{th} attribute of the i^{th} alternative. Suppose that there are k DMs, denoted by $C = \{C_1, \ldots, C_k\}$, with a weight vector $\lambda = (\lambda_1, \ldots, \lambda_k)$, where $\lambda_t \geq 0$ and $\sum_{t=1}^{k} \lambda_t = 1$. The SVN decision matrix is denoted by $R = (a_{ij})_{m \times n}$, where $a_{ij}^t = (T_{a_{ij}^t}, I_{a_{ij}^t}, F_{a_{ij}^t})$ encapsulates the evaluation details from the t^{th} decision-maker (DM). In this context, $T_{a_{ij}^t}$ represents the truth-membership function for attribute B_j of alternative A_i, as assessed by the t^{th} DM. Similarly, $I_{a_{ij}^t}$ denotes the indeterminacy-membership function, and $F_{a_{ij}^t}$ indicates the falsity-membership function for that same attribute. The original evaluation information provided by t^{th} DM is presented in Table I.

TABLE I
DECISION INFORMATION OF t^{TH} DECISION-MAKER

X	B_1	B_2	$\cdots$	B_n
A_1	(T_{11}, I_{11}, F_{11})	(T_{12}, I_{12}, F_{12})	$\cdots$	(T_{1n}, I_{1n}, F_{1n})
A_2	(T_{21}, I_{21}, F_{21})	(T_{22}, I_{22}, F_{22})	$\cdots$	(T_{2n}, I_{2n}, F_{2n})
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
A_m	(T_{m1}, I_{m1}, F_{m1})	(T_{m2}, I_{m2}, F_{m2})	$\cdots$	(T_{mn}, I_{mn}, F_{mn})

B. Weight Determination Method Based on Entropy

The traditional entropy weight method calculates the information entropy of identical attributes across all schemes, resulting in a fixed weight vector. Consequently, it assumes the same level of importance for identical attributes in different schemes, failing to account for the DM's preferences regarding the relationships between schemes and attributes. To address this limitation, this paper introduces a novel two-dimensional weight determination method based on the original entropy weight method.

Information pertaining to each attribute is evaluated within a consistent analytical framework. According to Equation (8), the entropy of alternative A_i $(i = 1, \ldots, m)$ is calculated as follows:

$$E_{ij}(A_i) = 1 - \frac{1}{k} \sum_{t=1}^{k} \left((T_{a_{ij}^t} + F_{a_{ij}^t}) \cdot \left| I_{a_{ij}^t} - I_{(a_{ij}^t)^c} \right| \right) \tag{18}$$

The weight of attribute j for alternative i is given by:

$$w_{ij} = \frac{1 - E_{ij}(A_i)}{\sum_{j=1}^{n} (1 - E_{ij}(A_i))}, \quad (j = 1, \ldots, n) \tag{19}$$

The above calculation steps are summarized in Table II.

TABLE II
PROCEDURE FOR ATTRIBUTE WEIGHT DETERMINATION

Calculation procedure		B_1	B_2	$\cdots$	B_n
Step 1	A_i	a_{i1}^1	a_{i2}^1	$\cdots$	a_{in}^1
		a_{i1}^2	a_{i2}^2	$\cdots$	a_{in}^2
		$\vdots$	$\vdots$	$\ddots$	$\vdots$
		a_{i1}^k	a_{i2}^k	$\cdots$	a_{in}^k
Step 2	A_i	E_{i1}	E_{i2}	$\cdots$	E_{in}
Step 3	A_i	w_{i1}	w_{i2}	$\cdots$	w_{in}

Example Assume there are two alternatives, $A = \{A_1, A_2\}$ and three attributes, $B = \{B_1, B_2, B_3\}$, with the following evaluation information provided by three DMs:

$$R^1 = \begin{bmatrix} (0.8, 0.1, 0.3) & (0.6, 0.2, 0.4) & (0.7, 0.3, 0.2) \\ (0.9, 0.1, 0.1) & (0.5, 0.4, 0.5) & (0.6, 0.5, 0.4) \end{bmatrix}$$

$$R^2 = \begin{bmatrix} (0.7, 0.2, 0.4) & (0.8, 0.1, 0.2) & (0.5, 0.3, 0.5) \\ (0.4, 0.5, 0.6) & (0.6, 0.4, 0.3) & (0.9, 0.2, 0.1) \end{bmatrix}$$

$$R^3 = \begin{bmatrix} (0.6, 0.3, 0.2) & (0.8, 0.2, 0.1) & (0.7, 0.2, 0.3) \\ (0.3, 0.6, 0.4) & (0.5, 0.5, 0.4) & (0.7, 0.1, 0.2) \end{bmatrix}$$

The values of the entropy matrix E are computed according to Equation (18).

$$E = \begin{bmatrix} 0.38 & 0.353 & 0.547 \\ 0.687 & 0.873 & 0.56 \end{bmatrix}$$

Using Equation (19), the weights are as follows: $w(A_1) = (0.36, 0.376, 0.264), w(A_2) = (0.356, 0.144, 0.5)$. In alternative A_1, the attribute weight ranking is B_2 (37.6%) $> B_1 > B_3$; whereas in alternative A_2, the ranking is $B_3 > B_1 > B_2$ (14.4%). These results demonstrate significant variability in attribute weights across alternatives. Furthermore, the preferences of DMs for attributes are dynamically adjusted based on the characteristics of the alternatives, illustrating a more realistic decision-making process.

C. Truncated Mean Approach in the SVNS Environment

We introduce a truncated mean approach to the SVNS environment, addressing the limitations of weight dependency and extreme-value sensitivity in traditional methods.

The detailed algorithmic procedure is outlined below.

Input: The SVNN set for alternative A_i, represented as $\{(T_{ij}, I_{ij}, F_{ij})\}_{j=1}^{n}$.

Output: Aggregated SVNS information for alternative A_i.

1) **Step 1:** Sort the SVNNs based on $s(A_{ij})$ in ascending order according to Equation (4).
2) **Step 2:** Remove the k largest and smallest extreme values (default $k = 1$, for $n \geq 5$, $k = \lfloor 0.2n \rfloor$), where $\lfloor 0.2n \rfloor$ denotes the floor function, which rounds down to the nearest integer.
3) **Step 3:** Compute the arithmetic mean of the remaining SVNNs according to Equation (20).

$$\tilde{A}_i = \frac{1}{n-2k} \left(\sum_{j=1}^{n-2k} T_{ij}, \sum_{j=1}^{n-2k} I_{ij}, \sum_{j=1}^{n-2k} F_{ij} \right) \quad (20)$$

Example Let $X = \{a, b, c, d\}$ be the universe of SVNS, and $Y = \{a_1, b_1, c_1, d_1\}$ denotes the corresponding score function. The set X is given as follows:

$$X = \left\{ \begin{array}{c} (0.9, 0.1, 0.1), \\ (0.8, 0.2, 0.1), \\ (0.7, 0.2, 0.2), \\ (0.65, 0.35, 0.3) \end{array} \right\}$$

The scores can be calculated using Equation (4):

$$Y = \{0.9, 0.83, 0.76, 0.67\}$$

Following score sorting Y_i $(i = 1, \ldots, 4)$, the second and third ranked values correspond to $b = (0.8, 0.2, 0.1)$ and $c = (0.7, 0.2, 0.2)$ respectively. Therefore, the aggregate SVNNs will be:

$$\tilde{A}_i = (0.75, 0.2, 0.15)$$

The truncated mean approach filters out extreme evaluations (e.g., by discarding the highest and lowest k SVNS ratings) before aggregation, thereby reducing sensitivity to outlier inputs.

V. The Proposed Approach for Solving MAGDM Problems Using TOPSIS

In this section, we integrate the innovative weight determination method and the truncated mean approach into the TOPSIS framework to formulate a MAGDM model.

Step 1: Assess the weight of decision-makers.

Let there be k DMs, where $c_t = (T_t, I_t, F_t)$ represents the t^{th} DM's SVNN information. The importance is determined using Equation (21).

$$\lambda_t = \frac{T_t + I_t \left(\frac{T_t}{T_t + F_t} \right)}{\sum_{t=1}^{k} \left(T_t + I_t \left(\frac{T_t}{T_t + F_t} \right) \right)} \quad (21)$$

Where $\lambda_t \geq 0$ and $\sum_{t=1}^{k} \lambda_t = 1$. This equation captures the interrelationships among the three membership functions for each DM.

Step 2: Construct a two-dimensional weight matrix for attributes of alternatives. Each attribute may have varying levels of importance across different alternatives. The weight matrix W can be calculated using Equations (18) and (19).

Step 3: Aggregate SVNNs of each decision-maker.

The decision matrix R^t is aggregated using the operator defined in Equation (2). Let $R^t = a_{ij}^t = (T_{a_{ij}^t}, I_{a_{ij}^t}, F_{a_{ij}^t})$ represent the evaluation matrix of the t^{th} DM. The aggregated matrix R is given by:

$$R = \sum_{t=1}^{k} \lambda_t R^t \quad (22)$$

Where $R = r_{ij} = (T_{ij}, I_{ij}, F_{ij})$ is computed as follows:

$$r_{ij} = \left(1 - \prod_{t=1}^{k} \left(1 - T_{ij}^t\right)^{\lambda_t}, \prod_{t=1}^{k} \left(I_{ij}^t\right)^{\lambda_t}, \prod_{t=1}^{k} F_{ij}^{t\ \lambda_t} \right)$$

Step 4: Formulate the aggregated weighted SVN decision matrix.

Let $U = U_{ij}$, with the weight matrix W applied in conjunction with the decision matrix R. Thus, U is represented as:

$$U = R \odot W \quad (23)$$

This process involves element-wise multiplication of the matrices obtained in Steps 2 and 3, as defined by the following equation:

$$U_{ij} = w_{ij} \cdot r_{ij} = (T'_{ij}, I'_{ij}, F'_{ij}) \quad (24)$$

Step 5: Determine A^+ and A^-.

The ideal solutions A^+ and A^- are determined by applying Equations (13) and (14) to the ordered set obtained from Equations (4), (5) and (6), with z_j^+ and z_j^- expressed as SVNNs.

Step 6: Aggregate the PIS and NIS separately.

We define $A'^+ = (T^+, I^+, F^+)$ and $A'^- = (T^-, I^-, F^-)$ to represent the PIS and NIS, respectively. The formulas for calculating are as follows:

For the NIS A'^-,

$$T^- = \min(T'_{ij}), I^- = \max(I'_{ij}), F^- = \max(F'_{ij}) \quad (25)$$

where $T'_{ij}, I'_{ij}, F'_{ij} \in A^-$.

For the PIS A'^+,

$$T^+ = \max(T'_{ij}), I^+ = \min(I'_{ij}), F^+ = \min(F'_{ij}) \quad (26)$$

where $T'_{ij}, I'_{ij}, F'_{ij} \in A^+$.

Step 7: Aggregate weighted SVNS information for each alternative.

The aggregation information of alternative A_i can be calculated using Equation (20).

Step 8: Calculate the distance for each alternative.

The distance D^+ between the alternative A_i and the PIS A'^+, as well as the distance D^- between A_i and the NIS A'^-, can be calculated using Equation (9).

$$\begin{cases} D_i^+ = \sum_{j=1}^{n} d\left(\tilde{A}_i, A'^+\right), \\ D_i^- = \sum_{j=1}^{n} d\left(\tilde{A}_i, A'^-\right), \end{cases} \quad i = 1, \ldots, m \tag{27}$$

Step 9: Calculate the relative closeness coefficient

The relative closeness coefficient S_i is determined using Equation (17). A detailed example will be provided to demonstrate the effectiveness and practical application of this method.

A. Illustrative Example

Assume that a company plans to invest in establishing a factory at a new location. Following preliminary investigations, the company has identified five viable plans. To facilitate the decision-making process, the company has convened a panel of three experts. These experts will evaluate the alternatives based on four key attributes: product quality, service level, customer satisfaction, and risk resistance capability. The sets of alternatives, attributes, and experts are denoted as $A = \{A_1, A_2, A_3, A_4, A_5\}$, $B = \{B_1, B_2, B_3, B_4\}$, $C = \{C_1, C_2, C_3\}$, respectively. The weight assigned to each expert is denoted by λ_t, where $\sum_{t=1}^{3} \lambda_t = 1$. The set of evaluation information for the experts is $C = \{(0.5, 0.4, 0.5), (0.8, 0.4, 0.5), (0.9, 0.9, 0.1)\}$. Let $R^t = a_{ij}^t = (T_{a_{ij}^t}, I_{a_{ij}^t}, F_{a_{ij}^t})$ represent the evaluation result of the t^{th} DM. The outcomes are presented in matrices R^1 to R^3.

Step 1: According to Equation (21), the weight vector is given by $\lambda = (0.203, 0.303, 0.495)$.

Step 2: The entropy matrix E is computed using Equation (18), as follows:

$$E = \begin{bmatrix} 0.4 & 0.353 & 0.107 & 0.313 \\ 0.48 & 0.54 & 0.66 & 0.54 \\ 0.353 & 0.353 & 0.233 & 0.313 \\ 0.82 & 0.393 & 0.107 & 0.167 \\ 0.14 & 0.34 & 0.207 & 0.52 \end{bmatrix}$$

Thus, the weight matrix W, derived from the matrix above, is represented as follows according to Equation (19):

$$W = \begin{bmatrix} 0.341 & 0.301 & 0.091 & 0.267 \\ 0.216 & 0.243 & 0.297 & 0.243 \\ 0.282 & 0.282 & 0.186 & 0.250 \\ 0.552 & 0.265 & 0.072 & 0.112 \\ 0.116 & 0.282 & 0.171 & 0.431 \end{bmatrix}$$

For example, $w_1 = (0.341, 0.301, 0.091, 0.267)$ represents the weight of each attribute for A_1.

Step 3: The decision matrix R is computed using Equation (22).

Step 4: The final comprehensive matrix U, derived from Equation (23), is obtained.

Step 5: Equations (4), (5) and (6) are employed to sort the elements of matrix U and derive the score matrix S.

$$S = \begin{bmatrix} 0.621 & 0.667 & 0.655 & 0.630 \\ 0.696 & 0.692 & 0.678 & 0.709 \\ 0.638 & 0.619 & 0.673 & 0.675 \\ 0.732 & 0.658 & 0.662 & 0.656 \\ 0.655 & 0.619 & 0.661 & 0.580 \end{bmatrix}.$$

Subsequently, A^+ and A^- for the criteria C_1, C_2, C_3, and C_4 can be calculated.

$$A_1^+ = (0.435, 0.063, 0.175), \quad A_1^- = (0.163, 0.261, 0.039)$$
$$A_2^+ = (0.166, 0.037, 0.053), \quad A_2^- = (0.135, 0.188, 0.09)$$
$$A_3^+ = (0.203, 0.046, 0.124), \quad A_3^- = (0.025, 0.051, 0.01)$$
$$A_4^+ = (0.192, 0.037, 0.028), \quad A_4^- = (0.206, 0.33, 0.137)$$

Step 6: The PIS and NIS are given by Equations (25) and (26) as follows:

$$A^+ = (0.435, 0.037, 0.028)$$
$$A^- = (0.025, 0.33, 0.137)$$

Step 7: Based on matrix U, $\tilde{A}_i$ is calculated using Equation (20), and the results are presented as follows

$$\tilde{A}_1 = (0.076, 0.115, 0.034)$$
$$\tilde{A}_2 = (0.157, 0.035, 0.039)$$
$$\tilde{A}_3 = (0.126, 0.118, 0.041)$$
$$\tilde{A}_4 = (0.09, 0.048, 0.064)$$
$$\tilde{A}_5 = (0.087, 0.135, 0.041)$$

Step 8: The distance calculated using Equation (27) are as follows:

$$D^+ = \{0.367, 0.279, 0.320, 0.347, 0.362\}$$
$$D^- = \{0.244, 0.338, 0.254, 0.299, 0.226\}$$

Step 9: The proximity coefficient S_i and rank order are displayed in Table III. The five alternatives were ranked as $A_2 > A_4 > A_3 > A_1 > A_5$. Therefore, A_2 was selected as the most suitable company to invest in.

TABLE III
RELATIVE CLOSENESS COEFFICIENT OF A_i

Alternatives	A_1	A_2	A_3	A_4	A_5
S_i	0.399	0.548	0.442	0.463	0.384
Rank	4	1	3	2	5

VI. COMPARATIVE ANALYSIS

To showcase the effectiveness of the proposed method, we compare it with several existing methods from the literature using the same case. The results are summarized in Table IV and visualized in Fig. 2. Fig. 3 offers an analysis of the attribute weight calculations, while Fig. 4 displays the weight information obtained through the proposed new method.

Ye [18] introduced a similarity-based weighting model, where DM weights are derived from the similarity between the SVN decision matrix and the average matrix, and attribute

$$R^1 = \begin{bmatrix} (0.6,0.9,0.2) & (0.7,0.4,0.4) & (0.4,0.7,0.2) & (0.6,0.8,0.3) \\ (0.8,0.3,0.2) & (0.8,0.3,0.3) & (0.8,0.3,0.5) & (0.9,0.3,0.2) \\ (0.7,0.8,0.3) & (0.6,0.8,0.4) & (0.6,0.4,0.2) & (0.7,0.4,0.3) \\ (0.9,0.2,0.4) & (0.7,0.4,0.5) & (0.5,0.5,0.3) & (0.6,0.7,0.3) \\ (0.7,0.6,0.5) & (0.5,0.9,0.2) & (0.8,0.7,0.3) & (0.6,0.9,0.4) \end{bmatrix}$$

$$R^2 = \begin{bmatrix} (0.5,0.8,0.1) & (0.6,0.3,0.3) & (0.3,0.6,0.1) & (0.5,0.7,0.2) \\ (0.7,0.2,0.1) & (0.7,0.2,0.2) & (0.7,0.2,0.4) & (0.8,0.2,0.1) \\ (0.6,0.7,0.2) & (0.5,0.7,0.3) & (0.5,0.3,0.1) & (0.6,0.3,0.2) \\ (0.8,0.1,0.3) & (0.6,0.3,0.4) & (0.4,0.4,0.2) & (0.5,0.6,0.2) \\ (0.6,0.5,0.4) & (0.4,0.8,0.1) & (0.7,0.6,0.2) & (0.5,0.8,0.3) \end{bmatrix}$$

$$R^3 = \begin{bmatrix} (0.4,0.7,0.1) & (0.5,0.2,0.3) & (0.2,0.5,0.1) & (0.4,0.6,0.2) \\ (0.6,0.1,0.1) & (0.6,0.1,0.2) & (0.6,0.1,0.4) & (0.7,0.1,0.1) \\ (0.5,0.6,0.2) & (0.4,0.6,0.3) & (0.4,0.2,0.1) & (0.5,0.2,0.2) \\ (0.7,0.1,0.3) & (0.5,0.2,0.4) & (0.3,0.3,0.2) & (0.4,0.5,0.2) \\ (0.5,0.4,0.4) & (0.3,0.7,0.1) & (0.6,0.5,0.2) & (0.4,0.7,0.3) \end{bmatrix}$$

$$R = \begin{bmatrix} (0.477,0.767,0.115) & (0.579,0.26,0.318) & (0.275,0.565,0.115) & (0.477,0.666,0.217) \\ (0.682,0.154,0.115) & (0.682,0.154,0.217) & (0.682,0.154,0.418) & (0.788,0.154,0.115) \\ (0.579,0.666,0.217) & (0.477,0.666,0.318) & (0.477,0.26,0.115) & (0.579,0.26,0.217) \\ (0.788,0.115,0.318) & (0.579,0.26,0.418) & (0.376,0.363,0.217) & (0.477,0.565,0.217) \\ (0.579,0.464,0.418) & (0.376,0.767,0.115) & (0.682,0.565,0.217) & (0.477,0.767,0.318) \end{bmatrix}.$$

$$U = \begin{bmatrix} (0.163,0.261,0.039) & (0.174,0.078,0.096) & (0.025,0.051,0.01) & (0.127,0.178,0.058) \\ (0.147,0.033,0.025) & (0.166,0.037,0.053) & (0.203,0.046,0.124) & (0.192,0.037,0.028) \\ (0.163,0.188,0.061) & (0.135,0.188,0.09) & (0.089,0.048,0.021) & (0.145,0.065,0.054) \\ (0.435,0.063,0.175) & (0.153,0.069,0.111) & (0.027,0.026,0.016) & (0.054,0.063,0.024) \\ (0.067,0.054,0.049) & (0.106,0.216,0.032) & (0.117,0.097,0.037) & (0.206,0.33,0.137) \end{bmatrix}.$$

TABLE IV
COMPARISON BETWEEN DIFFERENT METHODS

Methods	Ranking	The best alternative	The worst alternative
Ye [18]	$A_2 > A_4 > A_3 > A_1 > A_5$	A_2	A_5
Pramanik et al. [23]	$A_4 > A_2 > A_3 > A_1 > A_5$	A_4	A_5
Liu and Yang [9]	$A_2 > A_4 > A_3 > A_5 > A_1$	A_2	A_1
Biswas et al. [45]	$A_2 > A_1 > A_5 > A_3 > A_4$	A_2	A_4
The proposed model	$A_2 > A_4 > A_3 > A_1 > A_5$	A_2	A_5

importance is determined by comparing the matrix with its complement. Pramanik et al. [23] optimized attribute and DM weights by minimizing cross-entropy, yet their approach remains constrained by reliance on traditional aggregation operators. Liu and Yang [14] integrated the CRITIC method with EDAS to address attribute variability and correlation, but their framework requires predefined DM weights. Biswas et al. [45] advanced grey relational analysis by incorporating information entropy, utilizing weighted grey relational coefficients to assess attribute weight significance.

These models were selected for comparison due to their capability to handle MAGDM problems with unknown attribute weights. While they offer advantages in weight management or statistical integration, they share critical limitations: (1) Methods [14] and [45] cannot resolve unknown DM weights, restricting their applicability to MAGDM; (2) Methods [18] and [23], despite managing unknown weights, impose rigid single-vector weight structures that fail to capture DMs' dynamic preferences across alternatives; (3) All these methods depend on computationally intensive aggregation operators. The proposed method addresses these shortcomings by eliminating the structural rigidity of traditional weight vectors and the dependency on aggregation operators, achieving clearer alternative differentiation while aligning with established decision logic.

As shown in Fig. 2, alternative A2 is consistently ranked as optimal across most methods, except in Pramanik's model [23], where asymmetric weight determination introduces deviations. The comprehensive scores from our method fall within the range of those from the comparison models, avoiding the extreme cases observed in [23] and [14]. This

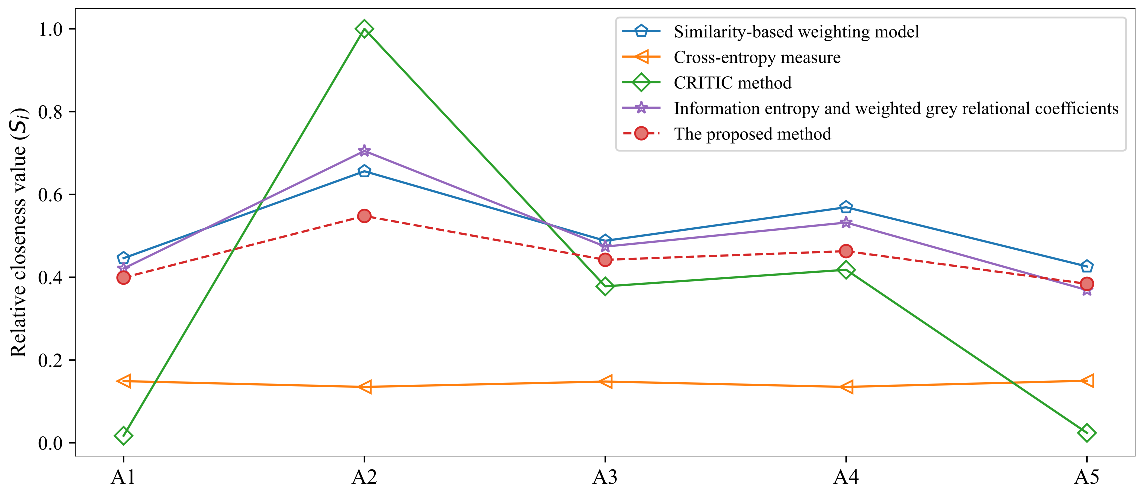

Fig. 2. Result comparisons between the five methods. A1–A5 represent five alternative options. Each colored line indicates the overall score of a specific alternative as determined by one of the methods.

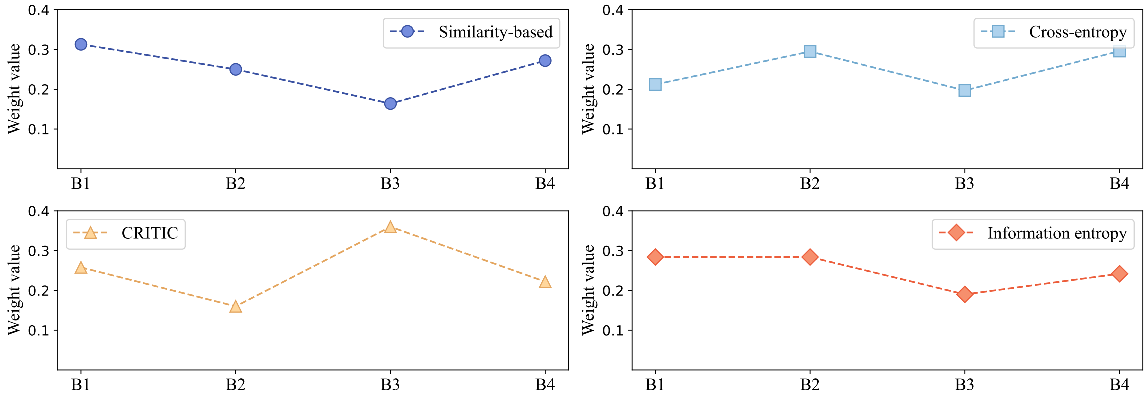

Fig. 3. Distribution of the attribute weight vector. B1–B4 represent product quality, service level, customer satisfaction, and risk resistance capability, respectively. Each subfigure illustrates the weights assigned by a different method.

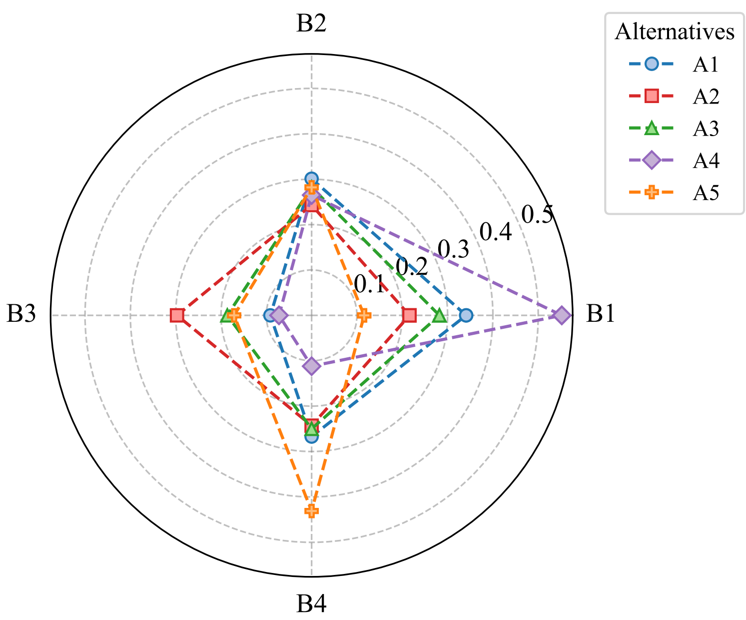

Fig. 4. Result of the weight matrix. Each radar line represents an alternative (A1–A5), showing its performance across the four attributes. Greater radial distance along an axis indicates stronger performance or higher importance of the corresponding attribute, while shorter distances imply weaker performance or lower relevance.

balanced distribution demonstrates the robustness of our approach in mitigating outlier behavior. Further analysis in Fig. 3 reveals a divergence in attributes B2 and B3 between other comparison methods and Liu and Yang's CRITIC-EDAS [14]. This divergence arises from their reliance on Pearson correlation coefficients, which assign negative weights to certain attributes, thereby diminishing their informational significance. Fig. 4 illustrates significant variations in criterion weights (B1–B4) across alternatives (A1–A5), reflecting the context-dependent nature of attribute prioritization. For example, alternative A1 assigns higher weights to B1 and B2 but lower importance to B3, whereas A4 exhibits a strong preference for B1. Our two-dimensional weight matrix effectively captures dynamic preference structures by explicitly modeling the importance of criteria specific to each alternative. This approach provides a more realistic and interpretable representation of decision-making behavior than conventional static weighting methods.

VII. Conclusion

This study proposes a dual-innovation framework for SVNS-based MAGDM, addressing two key challenges: the inflexibility of traditional vector-based weight representations in capturing dynamic attribute preferences of DMs across alternatives, and the over-reliance on weight dependency in existing operators. We propose (1) an entropy-driven two-dimensional weight matrix ($w_{ij} \in \mathbb{R}^{m\times n}$) to quantify the interdependent preferences between attributes and alternatives, and (2) a truncated mean aggregation mechanism that eliminates mandatory weight inputs through adaptive truncation of extreme values. Our method offers a more flexible and robust solution. The empirical weight variations observed in our experiments, in which the same attribute was assigned 37.6% for alternative A1 versus 14.4% for A2, demonstrate that our weight matrix outperforms traditional vector-based methods (e.g., entropy-based [45]) in distinguishing attribute preferences across alternatives. The framework, integrated with TOPSIS, proves especially effective in weight-ambiguous scenarios, where attribute weights are completely unknown or partially specified. Future extensions to interval neutrosophic set (INS) environments and behavioral economics-integrated models could further bridge theoretical advancements with real-world applications in supply chain optimization and medical decision support, ultimately laying the foundation for robust decision support in highly uncertain environments.

Author contributions

Dongsheng Xu conceived and designed the study, supervised the research, and provided critical revisions to the manuscript. Yuanyuan Peng conducted the experiments, wrote the manuscript, and revised it based on feedback. Lijuan Hu and Lin Jiang provided significant feedback and offered critical suggestions that improved the manuscript.

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