

4-20-2026

A Multi-Valued Rough Neutrosophic Approach for Multi-Criteria Decision-Making: Application in Hospital Selection

K. Gomathi

School of Advanced Sciences, Vellore Institute of Technology, Vellore, Tamil Nadu, India,
gomathi.k2023@vitstudent.ac.in

G. Deepa

School of Advanced Sciences, Vellore Institute of Technology, Vellore, Tamil Nadu, India,
deepa.g@vit.ac.in

Follow this and additional works at: <https://bsj.uobaghdad.edu.iq/home>

How to Cite this Article

Gomathi, K. and Deepa, G. (2026) "A Multi-Valued Rough Neutrosophic Approach for Multi-Criteria Decision-Making: Application in Hospital Selection," *Baghdad Science Journal*: Vol. 23: Iss. 4, Article 7. DOI: <https://doi.org/10.21123/2411-7986.5261>

This Article is brought to you for free and open access by Baghdad Science Journal. It has been accepted for inclusion in Baghdad Science Journal by an authorized editor of Baghdad Science Journal. For more information, please contact mina.t@csj.uobaghdad.edu.iq.



RESEARCH ARTICLE

A Multi-Valued Rough Neutrosophic Approach for Multi-Criteria Decision-Making: Application in Hospital Selection

K. Gomathi¹, G. Deepa¹ *

School of Advanced Sciences, Vellore Institute of Technology, Vellore, Tamil Nadu, India

ABSTRACT

Decision-making problems are often characterized by complexity and uncertainty, presenting significant challenges for individuals or organizations. Traditional aggregation methods often struggle with the imprecise, inconsistent, and unclear data found in these situations. To address these issues, this study proposes a new multi-criteria decision-making method based on Multi-Valued Rough Neutrosophic Numbers. We first introduce the fundamental operational laws for multi-valued rough neutrosophic numbers, based on t-norm and t-conorm. Subsequently, we establish four new multi-valued rough neutrosophic number-based aggregation operators: the Multi-Valued Rough Neutrosophic Arithmetic Mean Operator, the Weighted Multi-Valued Rough Neutrosophic Arithmetic Mean Operator, the Multi-Valued Rough Neutrosophic Geometric Mean Operator, and the Weighted Multi-Valued Rough Neutrosophic Geometric Mean Operator. We also prove that these proposed aggregation operators satisfy desirable properties, including monotonicity, idempotency, and boundedness. To determine the optimal weights of criteria, we utilize the Shapley fuzzy measure, capturing the significance and contribution of each criterion. Following this, specific score and accuracy functions are developed to facilitate the ranking of alternatives. Finally, a numerical illustration derived from a real-world hospital selection context is presented to demonstrate the effectiveness and practical utility of the proposed approach.

Keywords: Aggregation operators, Hospital selection, Multi-criteria decision-making, Multi-valued rough neutrosophic numbers, Rough neutrosophic set, Shapley fuzzy measure

Introduction

Decision-making problems, particularly in healthcare, are highly complex and involve significant ambiguity and uncertainty.^{1,2} Existing decision-making techniques struggle to handle imprecise information, which necessitates the development of more advanced methods. Zadeh³ introduced Fuzzy Sets to represent uncertainty through membership values. Later, Atanassov⁴ extended this concept by proposing Intuitionistic Fuzzy Sets with both membership and non-membership degrees. Smarandache⁵ introduced Neutrosophic Sets, characterized by truth, indeterminacy, and falsity components, which further led to the development of Single-Valued and Interval-Valued Neutrosophic Sets applicable in real-world situations. Peng and Wang⁶ introduced Multi-Valued Neutrosophic Sets (MVNS) with multiple values for each component.

Simultaneously, Pawlak⁷ introduced Rough Sets to handle incomplete information by using lower and upper approximations to define sets. Later, Dubois and Prade⁸ combined fuzzy and rough set methods. Broumi et al.⁹ then expanded rough sets to include neutrosophy, which led to the creation of neutrosophic rough

Received 18 April 2025; revised 9 September 2025; accepted 30 October 2025.
Available online 20 April 2026

* Corresponding author.

E-mail addresses: gomathi.k2023@vitstudent.ac.in (K. Gomathi), deepa.g@vit.ac.in (G. Deepa).

<https://doi.org/10.21123/2411-7986.5261>

2411-7986/© 2026 The Author(s). Published by College of Science for Women, University of Baghdad. This is an open-access article distributed under the terms of the Creative Commons Attribution 4.0 International License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

sets.¹⁰ These developments show the ongoing effort to improve how uncertainty is modeled. To enhance decision-making under these complex environments, various aggregation operators have been developed. Yao¹¹ introduced relational interpretations for rough sets. Key operators like t-norms and t-conorms were developed for fuzzy sets and extended by Atanassov to intuitionistic fuzzy sets, and by Smarandache¹² for neutrosophic sets. Rough neutrosophic aggregation operators were proposed by Mondal.¹³ Additionally, the Single-Valued Neutrosophic Dombi Weighted Aggregation Operators (SVNDWAO) have been introduced for multiple attribute decision-making, offering flexible aggregation structures.¹⁴ Other researchers also contributed by proposing new models, such as those combining ideas for Multi-Valued Rough Neutrosophic Sets (MVRNS).^{15,16} Awang et al.¹⁷ proposed a normalized Bonferroni mean operator using Shapley fuzzy measures. The Shapley value, introduced by Shapley,¹⁸ helps distribute gains fairly and was adapted to fuzzy environments for evaluating criteria importance.

Further advancements include geometric aggregation for single-valued neutrosophic hesitant fuzzy elements,¹⁹ hesitant complex neutrosophic sets (HCNS) and their distance measures,²⁰ and neutrosophic hesitant fuzzy multi-objective programming models.²¹ Matrix games with pay-offs have been applied in various neutrosophic settings, including single-valued,²² trapezoidal,²³ and interval neutrosophic matrices.²⁴ New models like correlation coefficients²⁵ and hypersoft sets²⁶ have improved handling of complex decision problems. Aggregation operators for material selection were developed by Farid and Riaz.²⁷ Fuzzy normed spaces help model uncertain data.²⁸ Multi-valued neutrosophic sets with power operators improve decision-making.²⁹

Neutrosophic rough sets continue to evolve for better decisions. Topological rough sets manage vague data, and cost-based models increase accuracy.³⁰ Neutrosophic matrices assist in site selection,³¹ and fuzzy rough sets support smart city plans.³² Group decisions are improved using confidence and two-universe models,^{33,34} and rough sets help in manufacturing choices.^{35,36} Jun Ye used algebraic and Einstein operators for complex decisions.³⁷ Kamran introduced Z-rough sine operators for industry evaluation.³⁸ Elsayed studied MCDM for economic assessment.³⁹ Xu and Zhao proposed a distance measure and used TOPSIS–TODIM for better results.⁴⁰ Ali and Bibi worked on waste reduction using neutrosophic rough sets.⁴¹ Alias et al. applied entropy-based multisets,⁴² and Halim et al. developed Shapley-Einstein operators for uncertain problems.⁴³ Yumashev et al.⁴⁴ proposed a rough neutrosophic and deep learning-based approach to improve kidney disease diagnosis. In a similar way, Pratheesha et al.⁴⁵ employed a TOPSIS technique based on quadripartitioned neutrosophic aggregation to make decisions with unclear data.

Despite these significant advancements, processing multi-valued, rough, and neutrosophic data within a coherent framework for complex decision-making processes remains a significant issue for current techniques. For instance, even when researching advanced neutrosophic clustering using distance measures⁴⁶ and sustainable management models,⁴⁷ or prioritizing options using type-2 neutrosophic numbers,⁴⁸ some studies might not accurately capture the multi-valued and rough components of expert judgments. While approaches using Muirhead Mean operators under complex single-valued neutrosophic values⁴⁹ or interdependency of complex fuzzy neighborhood operators⁵⁰ offer insights, a full framework combining all three dimensions is still being investigated. This gap is crucial because real-world expert assessments often require a more robust mathematical model due to their inherent roughness and incorporation of many uncertain opinions.

Furthermore, recent research on fuzzy linguistic Muirhead mean operators, which are used in neural networks,⁵¹ and soft covering-based sets,⁵² highlights the ongoing need for new aggregation methods in various areas. Research opportunities are also presented by the possibility of combining ideas such as Fuzzy Superior Mandelbrot Sets with Neutrosophic Sets, however this integration presents its own set of theoretical and practical difficulties. The range of issues needing complex MCDM tools is further illustrated by advanced aggregation operators such as those for renewable energy analysis,⁵³ disturbance observer-based control,⁵⁴ trust-driven consensus models,⁵⁵ and food waste treatment assessments.⁵⁶ Senapati⁵⁷ offered a strong framework for managing uncertainty by proposing an Aczel-Alsina aggregation-based outranking technique for multiple attribute decision-making utilizing single-valued neutrosophic numbers. Wang et al.⁵⁸ developed the Dual Generalized Single-Valued Neutrosophic Bonferroni Mean and the Dual Hesitant Single-Valued Neutrosophic Weighted Geometric Bonferroni Mean Operators. Liu and Zhang⁵⁹ introduced Neutrosophic Hesitant Fuzzy Heronian Mean Aggregation Operators, which are especially beneficial for capturing interrelationships among attributes in group decision-making.

To address this gap, this study proposes an MCDM method using MVRNNs. It introduces new aggregation operators, proves their properties, and uses the Shapley measure for optimal weights. New score and accuracy functions are developed, and a hospital selection example demonstrates their effectiveness.

Definition 1 (Neutrosophic Sets (NS)¹²): Let \mathbb{U} be the universal set, and each element $x \in \mathbb{U}$ has a degree of membership in the neutrosophic set \mathbb{S} that is Truth, Indeterminacy, and False. \mathbb{S} can be expressed as follows:

$$\mathbb{S} = \{(x, T_{\mathbb{S}}(x), I_{\mathbb{S}}(x), F_{\mathbb{S}}(x)) : x \in \mathbb{U}\},$$

Where $0 \leq T_{\mathbb{S}}(x) + I_{\mathbb{S}}(x) + F_{\mathbb{S}}(x) \leq 3$, and the membership functions are defined as follows: Truth Membership function $T_{\mathbb{S}} : \mathbb{U} \rightarrow [0, 1]$, Indeterminacy Membership function $I_{\mathbb{S}} : \mathbb{U} \rightarrow [0, 1]$, False Membership function $F_{\mathbb{S}} : \mathbb{U} \rightarrow [0, 1]$.

Definition 2 (Rough Set⁷): Let \mathbb{R} be an equivalence relation defined on the universal set \mathbb{U} . An approximation space is defined as $\mathbb{S} = \mathbb{U}/\mathbb{R}$, which is a collection of all equivalence classes of \mathbb{U} over \mathbb{R} .

Let $\mathbb{Y} \subseteq \mathbb{U}$ be a subset of \mathbb{U} . The terms $\underline{\mathbb{S}}(\mathbb{Y})$ and $\overline{\mathbb{S}}(\mathbb{Y})$, which stand for the lower and higher approximations of \mathbb{U} in \mathbb{S} respectively, are defined below.

$$\underline{\mathbb{S}}(\mathbb{Y}) = \{x \in \mathbb{U} : [x]_{\mathbb{R}} \subseteq \mathbb{Y}\}, \overline{\mathbb{S}}(\mathbb{Y}) = \{x \in \mathbb{U} : [x]_{\mathbb{R}} \cap \mathbb{Y} \neq \emptyset\}$$

where $[x]_{\mathbb{R}}$ represents the equivalence class of x under \mathbb{R} that contains an element x . The pair $\mathbb{S}(\mathbb{Y}) = (\underline{\mathbb{S}}(\mathbb{Y}), \overline{\mathbb{S}}(\mathbb{Y}))$ is known as a rough set of \mathbb{Y} in \mathbb{S} .

Definition 3 (Rough Neutrosophic Set⁹): Let \mathbb{U} be a universal set, and let each element $x \in \mathbb{U}$ be a member of a neutrosophic set \mathbb{S} , which includes membership functions for truth $T_{\mathbb{S}}$, indeterminacy $I_{\mathbb{S}}$, and falsity $F_{\mathbb{S}}$ in \mathbb{U} . Let \mathbb{R} be an equivalence relation on \mathbb{U} . Within the approximation space \mathbb{U}/\mathbb{R} , the lower and upper approximations of \mathbb{S} are denoted by $\underline{\mathbb{N}}(\mathbb{S})$ and $\overline{\mathbb{N}}(\mathbb{S})$, respectively, and have the following definitions:

$$\underline{\mathbb{N}}(\mathbb{S}) = \{\langle x, T_{\underline{\mathbb{N}}(\mathbb{S})}(x), I_{\underline{\mathbb{N}}(\mathbb{S})}(x), F_{\underline{\mathbb{N}}(\mathbb{S})}(x) \rangle : y \in [x]_{\mathbb{R}}, x \in \mathbb{U}\}$$

$$\overline{\mathbb{N}}(\mathbb{S}) = \{\langle x, T_{\overline{\mathbb{N}}(\mathbb{S})}(x), I_{\overline{\mathbb{N}}(\mathbb{S})}(x), F_{\overline{\mathbb{N}}(\mathbb{S})}(x) \rangle : y \in [x]_{\mathbb{R}}, x \in \mathbb{U}\}$$

where,

$$\begin{aligned} T_{\underline{\mathbb{N}}(\mathbb{S})}(x) &= \bigwedge_{y \in [x]_{\mathbb{R}}} T_{\mathbb{S}}(y) & T_{\overline{\mathbb{N}}(\mathbb{S})}(x) &= \bigvee_{y \in [x]_{\mathbb{R}}} T_{\mathbb{S}}(y) \\ I_{\underline{\mathbb{N}}(\mathbb{S})}(x) &= \bigvee_{y \in [x]_{\mathbb{R}}} I_{\mathbb{S}}(y) & I_{\overline{\mathbb{N}}(\mathbb{S})}(x) &= \bigwedge_{y \in [x]_{\mathbb{R}}} I_{\mathbb{S}}(y) \\ F_{\underline{\mathbb{N}}(\mathbb{S})}(x) &= \bigvee_{y \in [x]_{\mathbb{R}}} F_{\mathbb{S}}(y) & F_{\overline{\mathbb{N}}(\mathbb{S})}(x) &= \bigwedge_{y \in [x]_{\mathbb{R}}} F_{\mathbb{S}}(y) \end{aligned}$$

Additionally, the following conditions hold:

$$0 \leq T_{\underline{\mathbb{N}}(\mathbb{S})}(x) + I_{\underline{\mathbb{N}}(\mathbb{S})}(x) + F_{\underline{\mathbb{N}}(\mathbb{S})}(x) \leq 3 \text{ and } 0 \leq T_{\overline{\mathbb{N}}(\mathbb{S})}(x) + I_{\overline{\mathbb{N}}(\mathbb{S})}(x) + F_{\overline{\mathbb{N}}(\mathbb{S})}(x) \leq 3$$

$T_{\mathbb{S}}(x)$, $I_{\mathbb{S}}(x)$, and $F_{\mathbb{S}}(x)$ represent the truth, indeterminacy, and falsity membership functions, respectively, for the element x in the neutrosophic set \mathbb{S} . The symbols for the minimum and maximum operations are \wedge and \vee , respectively. Therefore $\underline{\mathbb{N}}(\mathbb{S})$ and $\overline{\mathbb{N}}(\mathbb{S})$ are two neutrosophic sets in \mathbb{U} . The rough neutrosophic set in the approximation space \mathbb{U}/\mathbb{R} is the pair $(\underline{\mathbb{N}}(\mathbb{S}), \overline{\mathbb{N}}(\mathbb{S}))$. If, for every $x \in \mathbb{U}$, $\underline{\mathbb{N}}(\mathbb{S}) = \overline{\mathbb{N}}(\mathbb{S})$, then \mathbb{S} is a defined neutrosophic set.

Definition 4 (Shapley Fuzzy Measure¹⁷): Let $\mathbb{Q} = \{1, 2, \dots, n\}$ be a set of criteria, and let $\mathbb{P}(\mathbb{Q})$ be its power set. A fuzzy measure μ is a function $\mu : \mathbb{P}(\mathbb{Q}) \rightarrow [0, 1]$ satisfying:

1. **Boundary:** $\mu(\emptyset) = 0, \mu(\mathbb{Q}) = 1$.
2. **Monotonicity:** If $\mathbb{A} \subseteq \mathbb{B}$, then $\mu(\mathbb{A}) \leq \mu(\mathbb{B})$.

A specific fuzzy measure, called the λ -fuzzy measure, is defined for disjoint sets \mathbb{A} and \mathbb{B} as:

$$\mu(\mathbb{A} \cup \mathbb{B}) = \mu(\mathbb{A}) + \mu(\mathbb{B}) - \lambda \mu(\mathbb{A})\mu(\mathbb{B}),$$

where $\lambda > -1$.

$$\mu_\lambda(\mathbb{A}) = \begin{cases} \frac{1}{\lambda} (\prod_{S_i \subseteq \mathbb{A}} (1 + \lambda \mu(\{S_i\})) - 1), & \text{if } \lambda \neq 0, \\ \sum_{S_i \subseteq \mathbb{A}} \mu(\{S_i\}), & \text{if } \lambda = 0. \end{cases}$$

The parameter λ can be computed as:

$$\prod_{S_i \subseteq \mathbb{A}} (1 + \lambda \mu(\{S_i\})) = \lambda + 1. \tag{1}$$

The Shapley fuzzy measure, representing the importance of each criterion, is computed as:

$$w_i = \sum_{W \subseteq Q \setminus \{i\}} \frac{(|Q| - |W| - 1)! |W|!}{|Q|!} (\mu(W \cup \{i\}) - \mu(W)). \tag{2}$$

It satisfies the property: $\sum_{i \in Q} w_i = 1$.

Definition 5 (Multi-Valued Rough Neutrosophic Set²): Let U be a universal set, and let each element $x \in U$ be associated with a neutrosophic set S , characterized by the truth membership degree $T_S(x)$, indeterminacy membership degree $I_S(x)$, and falsity membership degree $F_S(x)$. Let R denote an equivalence relation on U . Within the approximation space U/R , the lower and approximations of the neutrosophic set S are represented as $\underline{N}(S)$ and $\overline{N}(S)$, respectively. The following is the definition of these approximations:

$$\begin{aligned} \underline{N}(S) &= \{ \langle x, T_{\underline{N}(S)}(x), I_{\underline{N}(S)}(x), F_{\underline{N}(S)}(x) \rangle : y \in [x]_R \subseteq S, x \in U \}, \\ \overline{N}(S) &= \{ \langle x, T_{\overline{N}(S)}(x), I_{\overline{N}(S)}(x), F_{\overline{N}(S)}(x) \rangle : y \in [x]_R \cap S \neq \emptyset, x \in U \} \end{aligned}$$

The components $T_{\underline{N}(S)}(x)$, $I_{\underline{N}(S)}(x)$, and $F_{\underline{N}(S)}(x)$ for the lower approximation, as well as $T_{\overline{N}(S)}(x)$, $I_{\overline{N}(S)}(x)$, and $F_{\overline{N}(S)}(x)$ for the upper approximation, the values are computed as follows:

$$\begin{aligned} T_{\underline{N}(S)}(x) &= \bigwedge_{y \in [x]_R} T_S(y) & T_{\overline{N}(S)}(x) &= \bigvee_{y \in [x]_R} T_S(y) \\ I_{\underline{N}(S)}(x) &= \bigvee_{y \in [x]_R} I_S(y) & I_{\overline{N}(S)}(x) &= \bigwedge_{y \in [x]_R} I_S(y) \\ F_{\underline{N}(S)}(x) &= \bigvee_{y \in [x]_R} F_S(y) & F_{\overline{N}(S)}(x) &= \bigwedge_{y \in [x]_R} F_S(y) \end{aligned}$$

Here, \wedge and \vee denote the minimum and maximum operations, respectively. The following conditions hold:

$$0 \leq T_{\underline{N}(S)}(x) + I_{\underline{N}(S)}(x) + F_{\underline{N}(S)}(x) \leq 3, \quad 0 \leq T_{\overline{N}(S)}(x) + I_{\overline{N}(S)}(x) + F_{\overline{N}(S)}(x) \leq 3.$$

Furthermore, for any $x \in U$, let $\gamma \in T_S(x)$, $\eta \in I_S(x)$, $\xi \in F_S(x)$, and let $\gamma^+ = \sup T_S(x)$, $\eta^+ = \sup I_S(x)$, $\xi^+ = \sup F_S(x)$. These values satisfy:

$$0 \leq \gamma, \eta, \xi \leq 1, \quad 0 \leq \gamma^+ + \eta^+ + \xi^+ \leq 3.$$

The pair $(\underline{N}(S), \overline{N}(S))$ represents an MVRNS in U/R . If $\underline{N}(S) = \overline{N}(S)$ for any $x \in U$, then S is termed a definable MVNS.

Methodology

Multi-valued rough neutrosophic numbers and their operations

A Multi-Valued Rough Neutrosophic Number (MVRNN) builds on the concepts of rough and neutrosophic sets. This helps to better handle uncertainty, indeterminacy, and inconsistency in complex decision-making. Each element is assigned a set of truth, indeterminacy, and falsity values. To represent the inherent uncertainty, lower and upper approximations are then used. This feature makes MVRNNs especially useful when dealing with incomplete or conflicting information. This section will explain the basic operational rules and important properties of MVRNNs, specifically using Einstein operators.

We also establish several aggregation operators for MVRNNs, including the Multi-Valued Rough Neutrosophic Arithmetic Mean Operator, the Weighted Multi-Valued Rough Neutrosophic Arithmetic Mean Operator, the Multi-Valued Rough Neutrosophic Geometric Mean Operator, and the Weighted Multi-Valued Rough Neutrosophic Geometric Mean Operator.

Definition 6: Algebraic Operations on MVRNNs:

Let $N(S_1) = \langle (T_{N(S_1)}, I_{N(S_1)}, F_{N(S_1)}), (T_{\bar{N}(S_1)}, I_{\bar{N}(S_1)}, F_{\bar{N}(S_1)}) \rangle$ and

$N(S_2) = \langle (T_{N(S_2)}, I_{N(S_2)}, F_{N(S_2)}), (T_{\bar{N}(S_2)}, I_{\bar{N}(S_2)}, F_{\bar{N}(S_2)}) \rangle$,

be two MVRNNs. Then, the algebraic operations are defined as follows:

$$1. \lambda(N(S)) = \left\langle \left(\bigcup_{\gamma_{N(S)} \in T_{N(S)}} \left\{ \frac{(1+\gamma_{N(S)})^\lambda - (1-\gamma_{N(S)})^\lambda}{(1+\gamma_{N(S)})^\lambda + (1-\gamma_{N(S)})^\lambda} \right\}, \bigcup_{\eta_{N(S)} \in I_{N(S)}} \left\{ \frac{2(\eta_{N(S)})^\lambda}{(2-\eta_{N(S)})^\lambda + (\eta_{N(S)})^\lambda} \right\}, \bigcup_{\xi_{N(S)} \in F_{N(S)}} \left\{ \frac{2(\xi_{N(S)})^\lambda}{(2-\xi_{N(S)})^\lambda + (\xi_{N(S)})^\lambda} \right\} \right), \right. \\ \left. \left(\bigcup_{\gamma_{\bar{N}(S)} \in T_{\bar{N}(S)}} \left\{ \frac{(1+\gamma_{\bar{N}(S)})^\lambda - (1-\gamma_{\bar{N}(S)})^\lambda}{(1+\gamma_{\bar{N}(S)})^\lambda + (1-\gamma_{\bar{N}(S)})^\lambda} \right\}, \bigcup_{\eta_{\bar{N}(S)} \in I_{\bar{N}(S)}} \left\{ \frac{2(\eta_{\bar{N}(S)})^\lambda}{(2-\eta_{\bar{N}(S)})^\lambda + (\eta_{\bar{N}(S)})^\lambda} \right\}, \bigcup_{\xi_{\bar{N}(S)} \in F_{\bar{N}(S)}} \left\{ \frac{2(\xi_{\bar{N}(S)})^\lambda}{(2-\xi_{\bar{N}(S)})^\lambda + (\xi_{\bar{N}(S)})^\lambda} \right\} \right) \right\rangle.$$

$$2. [N(S)]^\lambda = \left\langle \left(\bigcup_{\gamma_{N(S)} \in T_{N(S)}} \left\{ \frac{2(\gamma_{N(S)})^\lambda}{(2-\gamma_{N(S)})^\lambda + (\gamma_{N(S)})^\lambda} \right\}, \bigcup_{\eta_{N(S)} \in I_{N(S)}} \left\{ \frac{(1+\eta_{N(S)})^\lambda - (1-\eta_{N(S)})^\lambda}{(1+\eta_{N(S)})^\lambda + (1-\eta_{N(S)})^\lambda} \right\}, \bigcup_{\xi_{N(S)} \in F_{N(S)}} \left\{ \frac{(1+\xi_{N(S)})^\lambda - (1-\xi_{N(S)})^\lambda}{(1+\xi_{N(S)})^\lambda + (1-\xi_{N(S)})^\lambda} \right\} \right), \right. \\ \left. \left(\bigcup_{\gamma_{\bar{N}(S)} \in T_{\bar{N}(S)}} \left\{ \frac{2(\gamma_{\bar{N}(S)})^\lambda}{(2-\gamma_{\bar{N}(S)})^\lambda + (\gamma_{\bar{N}(S)})^\lambda} \right\}, \bigcup_{\eta_{\bar{N}(S)} \in I_{\bar{N}(S)}} \left\{ \frac{(1+\eta_{\bar{N}(S)})^\lambda - (1-\eta_{\bar{N}(S)})^\lambda}{(1+\eta_{\bar{N}(S)})^\lambda + (1-\eta_{\bar{N}(S)})^\lambda} \right\}, \bigcup_{\xi_{\bar{N}(S)} \in F_{\bar{N}(S)}} \left\{ \frac{(1+\xi_{\bar{N}(S)})^\lambda - (1-\xi_{\bar{N}(S)})^\lambda}{(1+\xi_{\bar{N}(S)})^\lambda + (1-\xi_{\bar{N}(S)})^\lambda} \right\} \right) \right\rangle.$$

3. $N(S_1) \oplus N(S_2)$

$$= \left\langle \left(\bigcup_{\substack{\gamma_{N(S_1)} \in T_{N(S_1)} \\ \gamma_{N(S_2)} \in T_{N(S_2)}}} \left\{ \frac{\gamma_{N(S_1)} + \gamma_{N(S_2)}}{1 + \gamma_{N(S_1)}\gamma_{N(S_2)}} \right\}, \bigcup_{\substack{\eta_{N(S_1)} \in I_{N(S_1)} \\ \eta_{N(S_2)} \in I_{N(S_2)}}} \left\{ \frac{\eta_{N(S_1)}\eta_{N(S_2)}}{1 + (1-\eta_{N(S_1)})(1-\eta_{N(S_2)})} \right\}, \bigcup_{\substack{\xi_{N(S_1)} \in F_{N(S_1)} \\ \xi_{N(S_2)} \in F_{N(S_2)}}} \left\{ \frac{\xi_{N(S_1)}\xi_{N(S_2)}}{1 + (1-\xi_{N(S_1)})(1-\xi_{N(S_2)})} \right\} \right), \\ \left(\bigcup_{\substack{\gamma_{\bar{N}(S_1)} \in T_{\bar{N}(S_1)} \\ \gamma_{\bar{N}(S_2)} \in T_{\bar{N}(S_2)}}} \left\{ \frac{\gamma_{\bar{N}(S_1)} + \gamma_{\bar{N}(S_2)}}{1 + \gamma_{\bar{N}(S_1)}\gamma_{\bar{N}(S_2)}} \right\}, \bigcup_{\substack{\eta_{\bar{N}(S_1)} \in I_{\bar{N}(S_1)} \\ \eta_{\bar{N}(S_2)} \in I_{\bar{N}(S_2)}}} \left\{ \frac{\eta_{\bar{N}(S_1)}\eta_{\bar{N}(S_2)}}{1 + (1-\eta_{\bar{N}(S_1)})(1-\eta_{\bar{N}(S_2)})} \right\}, \bigcup_{\substack{\xi_{\bar{N}(S_1)} \in F_{\bar{N}(S_1)} \\ \xi_{\bar{N}(S_2)} \in F_{\bar{N}(S_2)}}} \left\{ \frac{\xi_{\bar{N}(S_1)}\xi_{\bar{N}(S_2)}}{1 + (1-\xi_{\bar{N}(S_1)})(1-\xi_{\bar{N}(S_2)})} \right\} \right) \right\rangle.$$

4. $N(S_1) \otimes N(S_2)$

$$= \left\langle \left(\bigcup_{\substack{\gamma_{N(S_1)} \in T_{N(S_1)} \\ \gamma_{N(S_2)} \in T_{N(S_2)}}} \left\{ \frac{\gamma_{N(S_1)} \cdot \gamma_{N(S_2)}}{1 + (1-\gamma_{N(S_1)})(1-\gamma_{N(S_2)})} \right\}, \bigcup_{\substack{\eta_{N(S_1)} \in I_{N(S_1)} \\ \eta_{N(S_2)} \in I_{N(S_2)}}} \left\{ \frac{\eta_{N(S_1)} + \eta_{N(S_2)}}{1 + \eta_{N(S_1)}\eta_{N(S_2)}} \right\}, \bigcup_{\substack{\xi_{N(S_1)} \in F_{N(S_1)} \\ \xi_{N(S_2)} \in F_{N(S_2)}}} \left\{ \frac{\xi_{N(S_1)} + \xi_{N(S_2)}}{1 + \xi_{N(S_1)}\xi_{N(S_2)}} \right\} \right), \\ \left(\bigcup_{\substack{\gamma_{\bar{N}(S_1)} \in T_{\bar{N}(S_1)} \\ \gamma_{\bar{N}(S_2)} \in T_{\bar{N}(S_2)}}} \left\{ \frac{\gamma_{\bar{N}(S_1)} \cdot \gamma_{\bar{N}(S_2)}}{1 + (1-\gamma_{\bar{N}(S_1)})(1-\gamma_{\bar{N}(S_2)})} \right\}, \bigcup_{\substack{\eta_{\bar{N}(S_1)} \in I_{\bar{N}(S_1)} \\ \eta_{\bar{N}(S_2)} \in I_{\bar{N}(S_2)}}} \left\{ \frac{\eta_{\bar{N}(S_1)} + \eta_{\bar{N}(S_2)}}{1 + \eta_{\bar{N}(S_1)}\eta_{\bar{N}(S_2)}} \right\}, \bigcup_{\substack{\xi_{\bar{N}(S_1)} \in F_{\bar{N}(S_1)} \\ \xi_{\bar{N}(S_2)} \in F_{\bar{N}(S_2)}}} \left\{ \frac{\xi_{\bar{N}(S_1)} + \xi_{\bar{N}(S_2)}}{1 + \xi_{\bar{N}(S_1)}\xi_{\bar{N}(S_2)}} \right\} \right) \right\rangle.$$

Definition 7. Properties of MVRNNs:

Let $N(S_1) = \langle (T_{N(S_1)}, I_{N(S_1)}, F_{N(S_1)}), (T_{\bar{N}(S_1)}, I_{\bar{N}(S_1)}, F_{\bar{N}(S_1)}) \rangle$, $N(S_2) = \langle (T_{N(S_2)}, I_{N(S_2)}, F_{N(S_2)}), (T_{\bar{N}(S_2)}, I_{\bar{N}(S_2)}, F_{\bar{N}(S_2)}) \rangle$, and $N(S_3) = \langle (T_{N(S_3)}, I_{N(S_3)}, F_{N(S_3)}), (T_{\bar{N}(S_3)}, I_{\bar{N}(S_3)}, F_{\bar{N}(S_3)}) \rangle$ be three MVRNNs. Then, the following properties hold:

1. $N(S_1) \oplus N(S_2) = N(S_2) \oplus N(S_1)$;

2. $N(S_1) \otimes N(S_2) = N(S_2) \otimes N(S_1)$;
3. $\lambda(N(S_1) \oplus N(S_2)) = \lambda N(S_1) \oplus \lambda N(S_2)$, $\lambda > 0$;
4. $(N(S_1) \otimes N(S_2))^\lambda = N(S_1)^\lambda \otimes N(S_2)^\lambda$, $\lambda > 0$;
5. $\lambda_1 N(S_1) \oplus \lambda_2 N(S_1) = (\lambda_1 + \lambda_2)N(S_1)$, $\lambda_1 > 0$, $\lambda_2 > 0$;
6. $N(S_1)^{\lambda_1} \otimes N(S_1)^{\lambda_2} = N(S_1)^{\lambda_1 + \lambda_2}$, $\lambda_1 > 0$, $\lambda_2 > 0$;
7. $(N(S_1) \oplus N(S_2)) \oplus N(S_3) = N(S_1) \oplus (N(S_2) \oplus N(S_3))$;
8. $(N(S_1) \otimes N(S_2)) \otimes N(S_3) = N(S_1) \otimes (N(S_2) \otimes N(S_3))$.

Proof:

1. $N(S_1) \oplus N(S_2)$

$$\begin{aligned}
 &= \left(\begin{array}{c} \bigcup_{\substack{\gamma_{\underline{N}}(s_1) \in T_{\underline{N}}(s_1) \\ \gamma_{\underline{N}}(s_2) \in T_{\underline{N}}(s_2)}} \left\{ \frac{\gamma_{\underline{N}}(s_1) + \gamma_{\underline{N}}(s_2)}{1 + \gamma_{\underline{N}}(s_1) \gamma_{\underline{N}}(s_2)} \right\}, \bigcup_{\substack{\eta_{\underline{N}}(s_1) \in I_{\underline{N}}(s_1) \\ \eta_{\underline{N}}(s_2) \in I_{\underline{N}}(s_2)}} \left\{ \frac{\eta_{\underline{N}}(s_1) \eta_{\underline{N}}(s_2)}{1 + (1 - \eta_{\underline{N}}(s_1))(1 - \eta_{\underline{N}}(s_2))} \right\}, \bigcup_{\substack{\xi_{\underline{N}}(s_1) \in F_{\underline{N}}(s_1) \\ \xi_{\underline{N}}(s_2) \in F_{\underline{N}}(s_2)}} \left\{ \frac{\xi_{\underline{N}}(s_1) \xi_{\underline{N}}(s_2)}{1 + (1 - \xi_{\underline{N}}(s_1))(1 - \xi_{\underline{N}}(s_2))} \right\} \end{array} \right) \\
 &= \left(\begin{array}{c} \bigcup_{\substack{\gamma_{\overline{N}}(s_1) \in T_{\overline{N}}(s_1) \\ \gamma_{\overline{N}}(s_2) \in T_{\overline{N}}(s_2)}} \left\{ \frac{\gamma_{\overline{N}}(s_1) + \gamma_{\overline{N}}(s_2)}{1 + \gamma_{\overline{N}}(s_1) \gamma_{\overline{N}}(s_2)} \right\}, \bigcup_{\substack{\eta_{\overline{N}}(s_1) \in I_{\overline{N}}(s_1) \\ \eta_{\overline{N}}(s_2) \in I_{\overline{N}}(s_2)}} \left\{ \frac{\eta_{\overline{N}}(s_1) \eta_{\overline{N}}(s_2)}{1 + (1 - \eta_{\overline{N}}(s_1))(1 - \eta_{\overline{N}}(s_2))} \right\}, \bigcup_{\substack{\xi_{\overline{N}}(s_1) \in F_{\overline{N}}(s_1) \\ \xi_{\overline{N}}(s_2) \in F_{\overline{N}}(s_2)}} \left\{ \frac{\xi_{\overline{N}}(s_1) \xi_{\overline{N}}(s_2)}{1 + (1 - \xi_{\overline{N}}(s_1))(1 - \xi_{\overline{N}}(s_2))} \right\} \end{array} \right) \\
 &= \left(\begin{array}{c} \bigcup_{\substack{\gamma_{\underline{N}}(s_2) \in T_{\underline{N}}(s_2) \\ \gamma_{\underline{N}}(s_1) \in T_{\underline{N}}(s_1)}} \left\{ \frac{\gamma_{\underline{N}}(s_2) + \gamma_{\underline{N}}(s_1)}{1 + \gamma_{\underline{N}}(s_2) \gamma_{\underline{N}}(s_1)} \right\}, \bigcup_{\substack{\eta_{\underline{N}}(s_2) \in I_{\underline{N}}(s_2) \\ \eta_{\underline{N}}(s_1) \in I_{\underline{N}}(s_1)}} \left\{ \frac{\eta_{\underline{N}}(s_2) \eta_{\underline{N}}(s_1)}{1 + (1 - \eta_{\underline{N}}(s_2))(1 - \eta_{\underline{N}}(s_1))} \right\}, \bigcup_{\substack{\xi_{\underline{N}}(s_2) \in F_{\underline{N}}(s_2) \\ \xi_{\underline{N}}(s_1) \in F_{\underline{N}}(s_1)}} \left\{ \frac{\xi_{\underline{N}}(s_2) \xi_{\underline{N}}(s_1)}{1 + (1 - \xi_{\underline{N}}(s_2))(1 - \xi_{\underline{N}}(s_1))} \right\} \end{array} \right) \\
 &= \left(\begin{array}{c} \bigcup_{\substack{\gamma_{\overline{N}}(s_2) \in T_{\overline{N}}(s_2) \\ \gamma_{\overline{N}}(s_1) \in T_{\overline{N}}(s_1)}} \left\{ \frac{\gamma_{\overline{N}}(s_2) + \gamma_{\overline{N}}(s_1)}{1 + \gamma_{\overline{N}}(s_2) \gamma_{\overline{N}}(s_1)} \right\}, \bigcup_{\substack{\eta_{\overline{N}}(s_2) \in I_{\overline{N}}(s_2) \\ \eta_{\overline{N}}(s_1) \in I_{\overline{N}}(s_1)}} \left\{ \frac{\eta_{\overline{N}}(s_2) \eta_{\overline{N}}(s_1)}{1 + (1 - \eta_{\overline{N}}(s_2))(1 - \eta_{\overline{N}}(s_1))} \right\}, \bigcup_{\substack{\xi_{\overline{N}}(s_2) \in F_{\overline{N}}(s_2) \\ \xi_{\overline{N}}(s_1) \in F_{\overline{N}}(s_1)}} \left\{ \frac{\xi_{\overline{N}}(s_2) \xi_{\overline{N}}(s_1)}{1 + (1 - \xi_{\overline{N}}(s_2))(1 - \xi_{\overline{N}}(s_1))} \right\} \end{array} \right) \\
 &= N(S_2) \oplus N(S_1).
 \end{aligned}$$

Similarly, it can be proved that the associative property holds:

$$(N(S_1) \oplus N(S_2)) \oplus N(S_3) = N(S_1) \oplus (N(S_2) \oplus N(S_3))$$

2. $N(S_1) \otimes N(S_2)$

$$\begin{aligned}
 &= \left(\begin{array}{c} \bigcup_{\substack{\gamma_{\underline{N}}(s_1) \in T_{\underline{N}}(s_1) \\ \gamma_{\underline{N}}(s_2) \in T_{\underline{N}}(s_2)}} \left\{ \frac{\gamma_{\underline{N}}(s_1) \cdot \gamma_{\underline{N}}(s_2)}{1 + (1 - \gamma_{\underline{N}}(s_1))(1 - \gamma_{\underline{N}}(s_2))} \right\}, \bigcup_{\substack{\eta_{\underline{N}}(s_1) \in I_{\underline{N}}(s_1) \\ \eta_{\underline{N}}(s_2) \in I_{\underline{N}}(s_2)}} \left\{ \frac{\eta_{\underline{N}}(s_1) + \eta_{\underline{N}}(s_2)}{1 + \eta_{\underline{N}}(s_1) \eta_{\underline{N}}(s_2)} \right\}, \bigcup_{\substack{\xi_{\underline{N}}(s_1) \in F_{\underline{N}}(s_1) \\ \xi_{\underline{N}}(s_2) \in F_{\underline{N}}(s_2)}} \left\{ \frac{\xi_{\underline{N}}(s_1) + \xi_{\underline{N}}(s_2)}{1 + \xi_{\underline{N}}(s_1) \xi_{\underline{N}}(s_2)} \right\} \end{array} \right) \\
 &= \left(\begin{array}{c} \bigcup_{\substack{\gamma_{\overline{N}}(s_1) \in T_{\overline{N}}(s_1) \\ \gamma_{\overline{N}}(s_2) \in T_{\overline{N}}(s_2)}} \left\{ \frac{\gamma_{\overline{N}}(s_1) \cdot \gamma_{\overline{N}}(s_2)}{1 + (1 - \gamma_{\overline{N}}(s_1))(1 - \gamma_{\overline{N}}(s_2))} \right\}, \bigcup_{\substack{\eta_{\overline{N}}(s_1) \in I_{\overline{N}}(s_1) \\ \eta_{\overline{N}}(s_2) \in I_{\overline{N}}(s_2)}} \left\{ \frac{\eta_{\overline{N}}(s_1) + \eta_{\overline{N}}(s_2)}{1 + \eta_{\overline{N}}(s_1) \eta_{\overline{N}}(s_2)} \right\}, \bigcup_{\substack{\xi_{\overline{N}}(s_1) \in F_{\overline{N}}(s_1) \\ \xi_{\overline{N}}(s_2) \in F_{\overline{N}}(s_2)}} \left\{ \frac{\xi_{\overline{N}}(s_1) + \xi_{\overline{N}}(s_2)}{1 + \xi_{\overline{N}}(s_1) \xi_{\overline{N}}(s_2)} \right\} \end{array} \right)
 \end{aligned}$$

$$= \left\langle \left(\begin{array}{c} \bigcup_{\substack{\gamma_{\mathbb{N}}(s_2) \in T_{\mathbb{N}}(s_2) \\ \gamma_{\mathbb{N}}(s_1) \in T_{\mathbb{N}}(s_1)}} \left\{ \frac{\gamma_{\mathbb{N}}(s_2) \cdot \gamma_{\mathbb{N}}(s_1)}{1 + (1 - \gamma_{\mathbb{N}}(s_2))(1 - \gamma_{\mathbb{N}}(s_1))} \right\}, \bigcup_{\substack{\eta_{\mathbb{N}}(s_2) \in I_{\mathbb{N}}(s_2) \\ \eta_{\mathbb{N}}(s_1) \in I_{\mathbb{N}}(s_1)}} \left\{ \frac{\eta_{\mathbb{N}}(s_2) + \eta_{\mathbb{N}}(s_1)}{1 + \eta_{\mathbb{N}}(s_2) \eta_{\mathbb{N}}(s_1)} \right\}, \bigcup_{\substack{\xi_{\mathbb{N}}(s_2) \in F_{\mathbb{N}}(s_2) \\ \xi_{\mathbb{N}}(s_1) \in F_{\mathbb{N}}(s_1)}} \left\{ \frac{\xi_{\mathbb{N}}(s_2) + \xi_{\mathbb{N}}(s_1)}{1 + \xi_{\mathbb{N}}(s_2) \xi_{\mathbb{N}}(s_1)} \right\} \right), \right. \\ \left. \left(\begin{array}{c} \bigcup_{\substack{\gamma_{\mathbb{N}}(s_2) \in T_{\mathbb{N}}(s_2) \\ \gamma_{\mathbb{N}}(s_1) \in T_{\mathbb{N}}(s_1)}} \left\{ \frac{\gamma_{\mathbb{N}}(s_2) \cdot \gamma_{\mathbb{N}}(s_1)}{1 + (1 - \gamma_{\mathbb{N}}(s_2))(1 - \gamma_{\mathbb{N}}(s_1))} \right\}, \bigcup_{\substack{\eta_{\mathbb{N}}(s_2) \in I_{\mathbb{N}}(s_2) \\ \eta_{\mathbb{N}}(s_1) \in I_{\mathbb{N}}(s_1)}} \left\{ \frac{\eta_{\mathbb{N}}(s_2) + \eta_{\mathbb{N}}(s_1)}{1 + \eta_{\mathbb{N}}(s_2) \eta_{\mathbb{N}}(s_1)} \right\}, \bigcup_{\substack{\xi_{\mathbb{N}}(s_2) \in F_{\mathbb{N}}(s_2) \\ \xi_{\mathbb{N}}(s_1) \in F_{\mathbb{N}}(s_1)}} \left\{ \frac{\xi_{\mathbb{N}}(s_2) + \xi_{\mathbb{N}}(s_1)}{1 + \xi_{\mathbb{N}}(s_2) \xi_{\mathbb{N}}(s_1)} \right\} \right) \right\rangle \\ = \mathbb{N}(S_2) \otimes \mathbb{N}(S_1) \end{array}$$

Similarly, it can be proved that the associative property holds:

$$(\mathbb{N}(S_1) \otimes \mathbb{N}(S_2)) \otimes \mathbb{N}(S_3) = \mathbb{N}(S_1) \otimes (\mathbb{N}(S_2) \otimes \mathbb{N}(S_3)).$$

(3) Since $\lambda > 0$,

$$\lambda \mathbb{N}(S_1) \oplus \lambda \mathbb{N}(S_2) = \left(\begin{array}{c} \bigcup_{\gamma_{\mathbb{N}}(s_1) \in T_{\mathbb{N}}(s_1)} \left\{ \frac{(1 + \gamma_{\mathbb{N}}(s_1))^\lambda - (1 - \gamma_{\mathbb{N}}(s_1))^\lambda}{(1 + \gamma_{\mathbb{N}}(s_1))^\lambda + (1 - \gamma_{\mathbb{N}}(s_1))^\lambda} \cdot \frac{(1 + \gamma_{\mathbb{N}}(s_2))^\lambda - (1 - \gamma_{\mathbb{N}}(s_2))^\lambda}{(1 + \gamma_{\mathbb{N}}(s_2))^\lambda + (1 - \gamma_{\mathbb{N}}(s_2))^\lambda} \right\}, \\ \bigcup_{\eta_{\mathbb{N}}(s_1) \in I_{\mathbb{N}}(s_1)} \left\{ \frac{2^{(\eta_{\mathbb{N}}(s_1))^\lambda}}{(2 - \eta_{\mathbb{N}}(s_1))^\lambda + (\eta_{\mathbb{N}}(s_1))^\lambda} - \frac{2^{(\eta_{\mathbb{N}}(s_2))^\lambda}}{(2 - \eta_{\mathbb{N}}(s_2))^\lambda + (\eta_{\mathbb{N}}(s_2))^\lambda} \right\}, \\ \bigcup_{\xi_{\mathbb{N}}(s_1) \in F_{\mathbb{N}}(s_1)} \left\{ \frac{2^{(\xi_{\mathbb{N}}(s_1))^\lambda}}{(2 - \xi_{\mathbb{N}}(s_1))^\lambda + (\xi_{\mathbb{N}}(s_1))^\lambda} - \frac{2^{(\xi_{\mathbb{N}}(s_2))^\lambda}}{(2 - \xi_{\mathbb{N}}(s_2))^\lambda + (\xi_{\mathbb{N}}(s_2))^\lambda} \right\} \right), \\ \left(\begin{array}{c} \bigcup_{\gamma_{\mathbb{N}}(s_1) \in T_{\mathbb{N}}(s_1)} \left\{ \frac{(1 + \gamma_{\mathbb{N}}(s_1))^\lambda - (1 - \gamma_{\mathbb{N}}(s_1))^\lambda}{(1 + \gamma_{\mathbb{N}}(s_1))^\lambda + (1 - \gamma_{\mathbb{N}}(s_1))^\lambda} \cdot \frac{(1 + \gamma_{\mathbb{N}}(s_2))^\lambda - (1 - \gamma_{\mathbb{N}}(s_2))^\lambda}{(1 + \gamma_{\mathbb{N}}(s_2))^\lambda + (1 - \gamma_{\mathbb{N}}(s_2))^\lambda} \right\}, \\ \bigcup_{\eta_{\mathbb{N}}(s_1) \in I_{\mathbb{N}}(s_1)} \left\{ \frac{2^{(\eta_{\mathbb{N}}(s_1))^\lambda}}{(2 - \eta_{\mathbb{N}}(s_1))^\lambda + (\eta_{\mathbb{N}}(s_1))^\lambda} - \frac{2^{(\eta_{\mathbb{N}}(s_2))^\lambda}}{(2 - \eta_{\mathbb{N}}(s_2))^\lambda + (\eta_{\mathbb{N}}(s_2))^\lambda} \right\}, \\ \bigcup_{\xi_{\mathbb{N}}(s_1) \in F_{\mathbb{N}}(s_1)} \left\{ \frac{2^{(\xi_{\mathbb{N}}(s_1))^\lambda}}{(2 - \xi_{\mathbb{N}}(s_1))^\lambda + (\xi_{\mathbb{N}}(s_1))^\lambda} - \frac{2^{(\xi_{\mathbb{N}}(s_2))^\lambda}}{(2 - \xi_{\mathbb{N}}(s_2))^\lambda + (\xi_{\mathbb{N}}(s_2))^\lambda} \right\} \right) \right) \\ = \left\langle \left(\begin{array}{c} \bigcup_{\gamma_{\mathbb{N}}(s_i) \in T_{\mathbb{N}}(s_i)} \left\{ \frac{(1 + \gamma_{\mathbb{N}}(s_1))^\lambda (1 + \gamma_{\mathbb{N}}(s_2))^\lambda - (1 - \gamma_{\mathbb{N}}(s_1))^\lambda (1 - \gamma_{\mathbb{N}}(s_2))^\lambda}{(1 + \gamma_{\mathbb{N}}(s_1))^\lambda (1 + \gamma_{\mathbb{N}}(s_2))^\lambda + (1 - \gamma_{\mathbb{N}}(s_1))^\lambda (1 - \gamma_{\mathbb{N}}(s_2))^\lambda} \right\}, \bigcup_{\eta_{\mathbb{N}}(s_i) \in I_{\mathbb{N}}(s_i)} \left\{ \frac{2^{(\eta_{\mathbb{N}}(s_1))^\lambda} (\eta_{\mathbb{N}}(s_2))^\lambda}{(2 - \eta_{\mathbb{N}}(s_1))^\lambda (2 - \eta_{\mathbb{N}}(s_2))^\lambda + (\eta_{\mathbb{N}}(s_1))^\lambda (\eta_{\mathbb{N}}(s_2))^\lambda} \right\}, \\ \bigcup_{\xi_{\mathbb{N}}(s_i) \in F_{\mathbb{N}}(s_i)} \left\{ \frac{2^{(\xi_{\mathbb{N}}(s_1))^\lambda} (\xi_{\mathbb{N}}(s_2))^\lambda}{(2 - \xi_{\mathbb{N}}(s_1))^\lambda (2 - \xi_{\mathbb{N}}(s_2))^\lambda + (\xi_{\mathbb{N}}(s_1))^\lambda (\xi_{\mathbb{N}}(s_2))^\lambda} \right\} \right), \\ \left(\begin{array}{c} \bigcup_{\gamma_{\mathbb{N}}(s_i) \in T_{\mathbb{N}}(s_i)} \left\{ \frac{(1 + \gamma_{\mathbb{N}}(s_1))^\lambda (1 + \gamma_{\mathbb{N}}(s_2))^\lambda - (1 - \gamma_{\mathbb{N}}(s_1))^\lambda (1 - \gamma_{\mathbb{N}}(s_2))^\lambda}{(1 + \gamma_{\mathbb{N}}(s_1))^\lambda (1 + \gamma_{\mathbb{N}}(s_2))^\lambda + (1 - \gamma_{\mathbb{N}}(s_1))^\lambda (1 - \gamma_{\mathbb{N}}(s_2))^\lambda} \right\}, \\ \bigcup_{\eta_{\mathbb{N}}(s_i) \in I_{\mathbb{N}}(s_i)} \left\{ \frac{2^{(\eta_{\mathbb{N}}(s_1))^\lambda} (\eta_{\mathbb{N}}(s_2))^\lambda}{(2 - \eta_{\mathbb{N}}(s_1))^\lambda (2 - \eta_{\mathbb{N}}(s_2))^\lambda + (\eta_{\mathbb{N}}(s_1))^\lambda (\eta_{\mathbb{N}}(s_2))^\lambda} \right\}, \\ \bigcup_{\xi_{\mathbb{N}}(s_i) \in F_{\mathbb{N}}(s_i)} \left\{ \frac{2^{(\xi_{\mathbb{N}}(s_1))^\lambda} (\xi_{\mathbb{N}}(s_2))^\lambda}{(2 - \xi_{\mathbb{N}}(s_1))^\lambda (2 - \xi_{\mathbb{N}}(s_2))^\lambda + (\xi_{\mathbb{N}}(s_1))^\lambda (\xi_{\mathbb{N}}(s_2))^\lambda} \right\} \right) \right\rangle \\ = \lambda \mathbb{N}(S_1) \oplus \lambda \mathbb{N}(S_2). \end{array}$$

Similarly, Eqs. (4) to (6) can be proved.

Aggregation operators

This section introduces the arithmetic and geometric mean aggregation operators specifically designed for MVRNNs. We also present a comprehensive methodology for applying these aggregation operators effectively in MCDM situations.

Definition 8 (Multi-Valued Rough Neutrosophic Arithmetic Mean Operator (A_{MVRN})): Let $N(S_i) = (\underline{N}(S_i), \bar{N}(S_i))$ for $i = 1, 2, \dots, n$ be a collection of MVRNNs. The Multi-Valued Rough Neutrosophic Arithmetic Mean Operator (A_{MVRN}) is then defined as:

$$A_{MVRN}(N(S_1), N(S_2), \dots, N(S_n)) = \left(\frac{1}{n} \bigoplus_{i=1}^n \underline{N}(S_i), \frac{1}{n} \bigoplus_{i=1}^n \bar{N}(S_i) \right)$$

Theorem 1: Let $N(S_i) = (\underline{N}(S_i), \bar{N}(S_i))$ for $i = 1, 2, \dots, n$ be a set of MVRNNs. The aggregated value obtained using the A_{MVRN} operator, defined as:

$$A_{MVRN}(N(S_1), N(S_2), \dots, N(S_n)) = \left(\frac{1}{n} \bigoplus_{i=1}^n \underline{N}(S_i), \frac{1}{n} \bigoplus_{i=1}^n \bar{N}(S_i) \right) \tag{3}$$

It is also an MVRNN.

$$= \left\langle \left(\bigcup_{\gamma_{\underline{N}(S_i)} \in \mathbb{T}_{\underline{N}(S_i)}} \left\{ \frac{\prod_{i=1}^n (1 + \gamma_{\underline{N}(S_i)})^{1/n} - \prod_{i=1}^n (1 - \gamma_{\underline{N}(S_i)})^{1/n}}{\prod_{i=1}^n (1 + \gamma_{\underline{N}(S_i)})^{1/n} + \prod_{i=1}^n (1 - \gamma_{\underline{N}(S_i)})^{1/n}} \right\}, \bigcup_{\eta_{\underline{N}(S_i)} \in \mathbb{I}_{\underline{N}(S_i)}} \left\{ \frac{2 \prod_{i=1}^n (\eta_{\underline{N}(S_i)})^{1/n}}{\prod_{i=1}^n (2 - \eta_{\underline{N}(S_i)})^{1/n} + \prod_{i=1}^n (\eta_{\underline{N}(S_i)})^{1/n}} \right\}, \right. \tag{4}$$

$$\left. \bigcup_{\xi_{\underline{N}(S_i)} \in \mathbb{F}_{\underline{N}(S_i)}} \left\{ \frac{2 \prod_{i=1}^n (\xi_{\underline{N}(S_i)})^{1/n}}{\prod_{i=1}^n (2 - \xi_{\underline{N}(S_i)})^{1/n} + \prod_{i=1}^n (\xi_{\underline{N}(S_i)})^{1/n}} \right\} \right), \left(\bigcup_{\gamma_{\bar{N}(S_i)} \in \mathbb{T}_{\bar{N}(S_i)}} \left\{ \frac{\prod_{i=1}^n (1 + \gamma_{\bar{N}(S_i)})^{1/n} - \prod_{i=1}^n (1 - \gamma_{\bar{N}(S_i)})^{1/n}}{\prod_{i=1}^n (1 + \gamma_{\bar{N}(S_i)})^{1/n} + \prod_{i=1}^n (1 - \gamma_{\bar{N}(S_i)})^{1/n}} \right\}, \right.$$

$$\left. \bigcup_{\eta_{\bar{N}(S_i)} \in \mathbb{I}_{\bar{N}(S_i)}} \left\{ \frac{2 \prod_{i=1}^n (\eta_{\bar{N}(S_i)})^{1/n}}{\prod_{i=1}^n (2 - \eta_{\bar{N}(S_i)})^{1/n} + \prod_{i=1}^n (\eta_{\bar{N}(S_i)})^{1/n}} \right\}, \bigcup_{\xi_{\bar{N}(S_i)} \in \mathbb{F}_{\bar{N}(S_i)}} \left\{ \frac{2 \prod_{i=1}^n (\xi_{\bar{N}(S_i)})^{1/n}}{\prod_{i=1}^n (2 - \xi_{\bar{N}(S_i)})^{1/n} + \prod_{i=1}^n (\xi_{\bar{N}(S_i)})^{1/n}} \right\} \right) \right\rangle.$$

Definition 9: Weighted Multi-Valued Rough Neutrosophic Arithmetic Mean Operator (A_{MVRN}^w)

Let $N(S_i) = (\underline{N}(S_i), \bar{N}(S_i))$ for $i = 1, 2, \dots, n$ be a collection of MVRNNs, and let $w = (w_1, w_2, \dots, w_n)$ be the weight vector for $N(S_1), N(S_2), \dots, N(S_n)$, such that $w_i \in [0, 1]$ and $\sum_{i=1}^n w_i = 1$. The Weighted Multi-Valued Rough Neutrosophic Arithmetic Mean Operator (A_{MVRN}^w) is then defined as:

$$A_{MVRN}^w(N(S_1), N(S_2), \dots, N(S_n)) = \left(\bigoplus_{i=1}^n w_i \underline{N}(S_i), \bigoplus_{i=1}^n w_i \bar{N}(S_i) \right)$$

Theorem 2: Let $N(S_i) = (\underline{N}(S_i), \bar{N}(S_i))$ for $(i = 1, 2, \dots, n)$ be a collection of MVRNNs, and let $w = (w_1, w_2, \dots, w_n)$ be the weight vector for $N(S_1), N(S_2), \dots, N(S_n)$, such that $w_i \in [0, 1]$ and $\sum_{i=1}^n w_i = 1$. The aggregated value obtained using the A_{MVRN}^w operator, defined as:

$$A_{MVRN}^w(N(S_1), N(S_2), \dots, N(S_n)) = \left(\bigoplus_{i=1}^n w_i \underline{N}(S_i), \bigoplus_{i=1}^n w_i \bar{N}(S_i) \right) \tag{5}$$

is also an MVRNN.

$$= \left\langle \left(\bigcup_{\gamma_{\underline{N}(S_i)} \in \mathbb{T}_{\underline{N}(S_i)}} \left\{ \frac{\prod_{i=1}^n (1 + \gamma_{\underline{N}(S_i)})^{w_i} - \prod_{i=1}^n (1 - \gamma_{\underline{N}(S_i)})^{w_i}}{\prod_{i=1}^n (1 + \gamma_{\underline{N}(S_i)})^{w_i} + \prod_{i=1}^n (1 - \gamma_{\underline{N}(S_i)})^{w_i}} \right\}, \bigcup_{\eta_{\underline{N}(S_i)} \in \mathbb{I}_{\underline{N}(S_i)}} \left\{ \frac{2 \prod_{i=1}^n (\eta_{\underline{N}(S_i)})^{w_i}}{\prod_{i=1}^n (2 - \eta_{\underline{N}(S_i)})^{w_i} + \prod_{i=1}^n (\eta_{\underline{N}(S_i)})^{w_i}} \right\}, \right. \tag{6}$$

$$\left. \bigcup_{\xi_{\underline{N}(S_i)} \in \mathbb{F}_{\underline{N}(S_i)}} \left\{ \frac{2 \prod_{i=1}^n (\xi_{\underline{N}(S_i)})^{w_i}}{\prod_{i=1}^n (2 - \xi_{\underline{N}(S_i)})^{w_i} + \prod_{i=1}^n (\xi_{\underline{N}(S_i)})^{w_i}} \right\} \right), \left(\bigcup_{\gamma_{\bar{N}(S_i)} \in \mathbb{T}_{\bar{N}(S_i)}} \left\{ \frac{\prod_{i=1}^n (1 + \gamma_{\bar{N}(S_i)})^{w_i} - \prod_{i=1}^n (1 - \gamma_{\bar{N}(S_i)})^{w_i}}{\prod_{i=1}^n (1 + \gamma_{\bar{N}(S_i)})^{w_i} + \prod_{i=1}^n (1 - \gamma_{\bar{N}(S_i)})^{w_i}} \right\}, \right.$$

$$\left. \bigcup_{\eta_{\bar{N}(S_i)} \in \mathbb{I}_{\bar{N}(S_i)}} \left\{ \frac{2 \prod_{i=1}^n (\eta_{\bar{N}(S_i)})^{w_i}}{\prod_{i=1}^n (2 - \eta_{\bar{N}(S_i)})^{w_i} + \prod_{i=1}^n (\eta_{\bar{N}(S_i)})^{w_i}} \right\}, \bigcup_{\xi_{\bar{N}(S_i)} \in \mathbb{F}_{\bar{N}(S_i)}} \left\{ \frac{2 \prod_{i=1}^n (\xi_{\bar{N}(S_i)})^{w_i}}{\prod_{i=1}^n (2 - \xi_{\bar{N}(S_i)})^{w_i} + \prod_{i=1}^n (\xi_{\bar{N}(S_i)})^{w_i}} \right\} \right) \right\rangle.$$

Proof: Using mathematical induction on n .

i) If $n = 2$, based on the operations Eqs. (1) and (3) in Definition 6,

$$w_1N(S_1) \oplus w_2N(S_2)$$

$$= \left(\begin{array}{l} \bigcup_{\gamma_N(S_1) \in \mathbb{T}_N(S_1)} \left\{ \frac{(1+\gamma_N(S_1))^{w_1} - (1-\gamma_N(S_1))^{w_1}}{(1+\gamma_N(S_1))^{w_1} + (1-\gamma_N(S_1))^{w_1}} \right\}, \bigcup_{\eta_N(S_1) \in \mathbb{I}_N(S_1)} \left\{ \frac{2(\eta_N(S_1))^{w_1}}{(2-\eta_N(S_1))^{w_1} + (\eta_N(S_1))^{w_1}} \right\}, \bigcup_{\xi_N(S_1) \in \mathbb{F}_N(S_1)} \left\{ \frac{2(\xi_N(S_1))^{w_1}}{(2-\xi_N(S_1))^{w_1} + (\xi_N(S_1))^{w_1}} \right\} \\ \bigcup_{\gamma_{\bar{N}}(S_1) \in \mathbb{T}_{\bar{N}}(S_1)} \left\{ \frac{(1+\gamma_{\bar{N}}(S_1))^{w_1} - (1-\gamma_{\bar{N}}(S_1))^{w_1}}{(1+\gamma_{\bar{N}}(S_1))^{w_1} + (1-\gamma_{\bar{N}}(S_1))^{w_1}} \right\}, \bigcup_{\eta_{\bar{N}}(S_1) \in \mathbb{I}_{\bar{N}}(S_1)} \left\{ \frac{2(\eta_{\bar{N}}(S_1))^{w_1}}{(2-\eta_{\bar{N}}(S_1))^{w_1} + (\eta_{\bar{N}}(S_1))^{w_1}} \right\}, \bigcup_{\xi_{\bar{N}}(S_1) \in \mathbb{F}_{\bar{N}}(S_1)} \left\{ \frac{2(\xi_{\bar{N}}(S_1))^{w_1}}{(2-\xi_{\bar{N}}(S_1))^{w_1} + (\xi_{\bar{N}}(S_1))^{w_1}} \right\} \end{array} \right) \oplus \left(\begin{array}{l} \bigcup_{\gamma_N(S_2) \in \mathbb{T}_N(S_2)} \left\{ \frac{(1+\gamma_N(S_2))^{w_2} - (1-\gamma_N(S_2))^{w_2}}{(1+\gamma_N(S_2))^{w_2} + (1-\gamma_N(S_2))^{w_2}} \right\}, \bigcup_{\eta_N(S_2) \in \mathbb{I}_N(S_2)} \left\{ \frac{2(\eta_N(S_2))^{w_2}}{(2-\eta_N(S_2))^{w_2} + (\eta_N(S_2))^{w_2}} \right\}, \bigcup_{\xi_N(S_2) \in \mathbb{F}_N(S_2)} \left\{ \frac{2(\xi_N(S_2))^{w_2}}{(2-\xi_N(S_2))^{w_2} + (\xi_N(S_2))^{w_2}} \right\} \\ \bigcup_{\gamma_{\bar{N}}(S_2) \in \mathbb{T}_{\bar{N}}(S_2)} \left\{ \frac{(1+\gamma_{\bar{N}}(S_2))^{w_2} - (1-\gamma_{\bar{N}}(S_2))^{w_2}}{(1+\gamma_{\bar{N}}(S_2))^{w_2} + (1-\gamma_{\bar{N}}(S_2))^{w_2}} \right\}, \bigcup_{\eta_{\bar{N}}(S_2) \in \mathbb{I}_{\bar{N}}(S_2)} \left\{ \frac{2(\eta_{\bar{N}}(S_2))^{w_2}}{(2-\eta_{\bar{N}}(S_2))^{w_2} + (\eta_{\bar{N}}(S_2))^{w_2}} \right\}, \bigcup_{\xi_{\bar{N}}(S_2) \in \mathbb{F}_{\bar{N}}(S_2)} \left\{ \frac{2(\xi_{\bar{N}}(S_2))^{w_2}}{(2-\xi_{\bar{N}}(S_2))^{w_2} + (\xi_{\bar{N}}(S_2))^{w_2}} \right\} \end{array} \right)$$

$$= \left(\begin{array}{l} \bigcup_{\gamma_N(S_1) \in \mathbb{T}_N(S_1), \gamma_N(S_2) \in \mathbb{T}_N(S_2)} \left\{ \frac{(1+\gamma_N(S_1))^{w_1} - (1-\gamma_N(S_1))^{w_1}}{(1+\gamma_N(S_1))^{w_1} + (1-\gamma_N(S_1))^{w_1}} + \frac{(1+\gamma_N(S_2))^{w_2} - (1-\gamma_N(S_2))^{w_2}}{(1+\gamma_N(S_2))^{w_2} + (1-\gamma_N(S_2))^{w_2}}}{1 + \frac{(1+\gamma_N(S_1))^{w_1} - (1-\gamma_N(S_1))^{w_1}}{(1+\gamma_N(S_1))^{w_1} + (1-\gamma_N(S_1))^{w_1}} \cdot \frac{(1+\gamma_N(S_2))^{w_2} - (1-\gamma_N(S_2))^{w_2}}{(1+\gamma_N(S_2))^{w_2} + (1-\gamma_N(S_2))^{w_2}}} \right\}, \\ \bigcup_{\eta_N(S_1) \in \mathbb{I}_N(S_1), \eta_N(S_2) \in \mathbb{I}_N(S_2)} \left\{ \frac{2(\eta_N(S_1))^{w_1}}{(2-\eta_N(S_1))^{w_1} + (\eta_N(S_1))^{w_1}} \cdot \frac{2(\eta_N(S_2))^{w_2}}{(2-\eta_N(S_2))^{w_2} + (\eta_N(S_2))^{w_2}}}{1 + \left(1 - \frac{2(\eta_N(S_1))^{w_1}}{(2-\eta_N(S_1))^{w_1} + (\eta_N(S_1))^{w_1}}\right) \cdot \left(1 - \frac{2(\eta_N(S_2))^{w_2}}{(2-\eta_N(S_2))^{w_2} + (\eta_N(S_2))^{w_2}}\right)} \right\}, \\ \bigcup_{\xi_N(S_1) \in \mathbb{F}_N(S_1), \xi_N(S_2) \in \mathbb{F}_N(S_2)} \left\{ \frac{2(\xi_N(S_1))^{w_1}}{(2-\xi_N(S_1))^{w_1} + (\xi_N(S_1))^{w_1}} \cdot \frac{2(\xi_N(S_2))^{w_2}}{(2-\xi_N(S_2))^{w_2} + (\xi_N(S_2))^{w_2}}}{1 + \left(1 - \frac{2(\xi_N(S_1))^{w_1}}{(2-\xi_N(S_1))^{w_1} + (\xi_N(S_1))^{w_1}}\right) \cdot \left(1 - \frac{2(\xi_N(S_2))^{w_2}}{(2-\xi_N(S_2))^{w_2} + (\xi_N(S_2))^{w_2}}\right)} \right\}, \\ \bigcup_{\gamma_{\bar{N}}(S_1) \in \mathbb{T}_{\bar{N}}(S_1), \gamma_{\bar{N}}(S_2) \in \mathbb{T}_{\bar{N}}(S_2)} \left\{ \frac{(1+\gamma_{\bar{N}}(S_1))^{w_1} - (1-\gamma_{\bar{N}}(S_1))^{w_1}}{(1+\gamma_{\bar{N}}(S_1))^{w_1} + (1-\gamma_{\bar{N}}(S_1))^{w_1}} + \frac{(1+\gamma_{\bar{N}}(S_2))^{w_2} - (1-\gamma_{\bar{N}}(S_2))^{w_2}}{(1+\gamma_{\bar{N}}(S_2))^{w_2} + (1-\gamma_{\bar{N}}(S_2))^{w_2}}}{1 + \frac{(1+\gamma_{\bar{N}}(S_1))^{w_1} - (1-\gamma_{\bar{N}}(S_1))^{w_1}}{(1+\gamma_{\bar{N}}(S_1))^{w_1} + (1-\gamma_{\bar{N}}(S_1))^{w_1}} \cdot \frac{(1+\gamma_{\bar{N}}(S_2))^{w_2} - (1-\gamma_{\bar{N}}(S_2))^{w_2}}{(1+\gamma_{\bar{N}}(S_2))^{w_2} + (1-\gamma_{\bar{N}}(S_2))^{w_2}}} \right\}, \\ \bigcup_{\eta_{\bar{N}}(S_1) \in \mathbb{I}_{\bar{N}}(S_1), \eta_{\bar{N}}(S_2) \in \mathbb{I}_{\bar{N}}(S_2)} \left\{ \frac{2(\eta_{\bar{N}}(S_1))^{w_1}}{(2-\eta_{\bar{N}}(S_1))^{w_1} + (\eta_{\bar{N}}(S_1))^{w_1}} \cdot \frac{2(\eta_{\bar{N}}(S_2))^{w_2}}{(2-\eta_{\bar{N}}(S_2))^{w_2} + (\eta_{\bar{N}}(S_2))^{w_2}}}{1 + \left(1 - \frac{2(\eta_{\bar{N}}(S_1))^{w_1}}{(2-\eta_{\bar{N}}(S_1))^{w_1} + (\eta_{\bar{N}}(S_1))^{w_1}}\right) \cdot \left(1 - \frac{2(\eta_{\bar{N}}(S_2))^{w_2}}{(2-\eta_{\bar{N}}(S_2))^{w_2} + (\eta_{\bar{N}}(S_2))^{w_2}}\right)} \right\}, \\ \bigcup_{\xi_{\bar{N}}(S_1) \in \mathbb{F}_{\bar{N}}(S_1), \xi_{\bar{N}}(S_2) \in \mathbb{F}_{\bar{N}}(S_2)} \left\{ \frac{2(\xi_{\bar{N}}(S_1))^{w_1}}{(2-\xi_{\bar{N}}(S_1))^{w_1} + (\xi_{\bar{N}}(S_1))^{w_1}} \cdot \frac{2(\xi_{\bar{N}}(S_2))^{w_2}}{(2-\xi_{\bar{N}}(S_2))^{w_2} + (\xi_{\bar{N}}(S_2))^{w_2}}}{1 + \left(1 - \frac{2(\xi_{\bar{N}}(S_1))^{w_1}}{(2-\xi_{\bar{N}}(S_1))^{w_1} + (\xi_{\bar{N}}(S_1))^{w_1}}\right) \cdot \left(1 - \frac{2(\xi_{\bar{N}}(S_2))^{w_2}}{(2-\xi_{\bar{N}}(S_2))^{w_2} + (\xi_{\bar{N}}(S_2))^{w_2}}\right)} \right\} \end{array} \right)$$

$$\mathbb{A}_{MVRN}(N(S_1), N(S_2))$$

$$= \left(\begin{array}{l} \bigcup_{\gamma_N(S_1) \in \mathbb{T}_N(S_1), \gamma_N(S_2) \in \mathbb{T}_N(S_2)} \left\{ \frac{(1+\gamma_N(S_1))^{w_1} (1+\gamma_N(S_2))^{w_2} - (1-\gamma_N(S_1))^{w_1} (1-\gamma_N(S_2))^{w_2}}{(1+\gamma_N(S_1))^{w_1} (1+\gamma_N(S_2))^{w_2} + (1-\gamma_N(S_1))^{w_1} (1-\gamma_N(S_2))^{w_2}} \right\}, \\ \bigcup_{\eta_N(S_1) \in \mathbb{I}_N(S_1), \eta_N(S_2) \in \mathbb{I}_N(S_2)} \left\{ \frac{2(\eta_N(S_1))^{w_1} (\eta_N(S_2))^{w_2}}{(2-\eta_N(S_1))^{w_1} (2-\eta_N(S_2))^{w_2} + (\eta_N(S_1))^{w_1} (\eta_N(S_2))^{w_2}} \right\}, \\ \bigcup_{\xi_N(S_1) \in \mathbb{F}_N(S_1), \xi_N(S_2) \in \mathbb{F}_N(S_2)} \left\{ \frac{2(\xi_N(S_1))^{w_1} (\xi_N(S_2))^{w_2}}{(2-\xi_N(S_1))^{w_1} (2-\xi_N(S_2))^{w_2} + (\xi_N(S_1))^{w_1} (\xi_N(S_2))^{w_2}} \right\}, \\ \bigcup_{\gamma_{\bar{N}}(S_1) \in \mathbb{T}_{\bar{N}}(S_1), \gamma_{\bar{N}}(S_2) \in \mathbb{T}_{\bar{N}}(S_2)} \left\{ \frac{(1+\gamma_{\bar{N}}(S_1))^{w_1} (1+\gamma_{\bar{N}}(S_2))^{w_2} - (1-\gamma_{\bar{N}}(S_1))^{w_1} (1-\gamma_{\bar{N}}(S_2))^{w_2}}{(1+\gamma_{\bar{N}}(S_1))^{w_1} (1+\gamma_{\bar{N}}(S_2))^{w_2} + (1-\gamma_{\bar{N}}(S_1))^{w_1} (1-\gamma_{\bar{N}}(S_2))^{w_2}} \right\}, \\ \bigcup_{\eta_{\bar{N}}(S_1) \in \mathbb{I}_{\bar{N}}(S_1), \eta_{\bar{N}}(S_2) \in \mathbb{I}_{\bar{N}}(S_2)} \left\{ \frac{2(\eta_{\bar{N}}(S_1))^{w_1} (\eta_{\bar{N}}(S_2))^{w_2}}{(2-\eta_{\bar{N}}(S_1))^{w_1} (2-\eta_{\bar{N}}(S_2))^{w_2} + (\eta_{\bar{N}}(S_1))^{w_1} (\eta_{\bar{N}}(S_2))^{w_2}} \right\}, \\ \bigcup_{\xi_{\bar{N}}(S_1) \in \mathbb{F}_{\bar{N}}(S_1), \xi_{\bar{N}}(S_2) \in \mathbb{F}_{\bar{N}}(S_2)} \left\{ \frac{2(\xi_{\bar{N}}(S_1))^{w_1} (\xi_{\bar{N}}(S_2))^{w_2}}{(2-\xi_{\bar{N}}(S_1))^{w_1} (2-\xi_{\bar{N}}(S_2))^{w_2} + (\xi_{\bar{N}}(S_1))^{w_1} (\xi_{\bar{N}}(S_2))^{w_2}} \right\} \end{array} \right)$$

Properties of aggregation operators

The A_{MVRN} and A_{MVRN}^w operators, along with their geometric counterparts, satisfy the following key properties:

Property 1 (Idempotency Law): If all MVRNNs are identical, i.e., $N(S_i) = N(S)$ for $i = 1, 2, \dots, n$, then:

$$A_{MVRN}(N(S_1), N(S_2), \dots, N(S_n)) = N(S)$$

and

$$A_{MVRN}^w(N(S_1), N(S_2), \dots, N(S_n)) = N(S).$$

Proof: For $N(S_i) = N(S)$, by definition of A_{MVRN} operator:

$$A_{MVRN}((N(S_1), \dots, N(S_n))) = \left(\frac{1}{n} \bigoplus_{i=1}^n \underline{N}(S), \frac{1}{n} \bigoplus_{i=1}^n \bar{N}(S) \right) = (\underline{N}(S), \bar{N}(S)) = N(S).$$

For A_{MVRN}^w operator, given $\sum_{i=1}^n w_i = 1$:

$$A_{MVRN}^w(N(S_1), \dots, N(S_n)) = \left(\bigoplus_{i=1}^n w_i \underline{N}(S), \bigoplus_{i=1}^n w_i \bar{N}(S) \right) = (\underline{N}(S), \bar{N}(S)) = N(S).$$

This holds because $\bigoplus_{i=1}^n w_i X = X$ when $\sum w_i = 1$ for any MVRNN X (based on the definition of weighted aggregation and scalar multiplication).

Property 2 (Boundedness): Both operators are bounded.

Proof: For $i = 1, 2, \dots, n$, let $N(S_i)$ be a set of MVRNNs. Construct the following lower and upper bounds: $N(S)^-$ and $N(S)^+$.

$$N(S)^- = \left\langle \left(\bigcup_{\gamma_{\underline{N}(S_i)} \in \mathbb{T}_{\underline{N}(S_i)}} \left\{ \min_i \gamma_{\underline{N}(S_i)} \right\}, \bigcup_{\eta_{\underline{N}(S_i)} \in \mathbb{I}_{\underline{N}(S_i)}} \left\{ \max_i \eta_{\underline{N}(S_i)} \right\}, \bigcup_{\xi_{\underline{N}(S_i)} \in \mathbb{F}_{\underline{N}(S_i)}} \left\{ \max_i \xi_{\underline{N}(S_i)} \right\} \right), \right. \\ \left. \left(\bigcup_{\gamma_{\bar{N}(S_i)} \in \mathbb{T}_{\bar{N}(S_i)}} \left\{ \min_i \gamma_{\bar{N}(S_i)} \right\}, \bigcup_{\eta_{\bar{N}(S_i)} \in \mathbb{I}_{\bar{N}(S_i)}} \left\{ \max_i \eta_{\bar{N}(S_i)} \right\}, \bigcup_{\xi_{\bar{N}(S_i)} \in \mathbb{F}_{\bar{N}(S_i)}} \left\{ \max_i \xi_{\bar{N}(S_i)} \right\} \right) \right\rangle.$$

and

$$N(S)^+ = \left\langle \left(\bigcup_{\gamma_{\underline{N}(S_i)} \in \mathbb{T}_{\underline{N}(S_i)}} \left\{ \max_i \gamma_{\underline{N}(S_i)} \right\}, \bigcup_{\eta_{\underline{N}(S_i)} \in \mathbb{I}_{\underline{N}(S_i)}} \left\{ \min_i \eta_{\underline{N}(S_i)} \right\}, \bigcup_{\xi_{\underline{N}(S_i)} \in \mathbb{F}_{\underline{N}(S_i)}} \left\{ \min_i \xi_{\underline{N}(S_i)} \right\} \right), \right. \\ \left. \left(\bigcup_{\gamma_{\bar{N}(S_i)} \in \mathbb{T}_{\bar{N}(S_i)}} \left\{ \max_i \gamma_{\bar{N}(S_i)} \right\}, \bigcup_{\eta_{\bar{N}(S_i)} \in \mathbb{I}_{\bar{N}(S_i)}} \left\{ \min_i \eta_{\bar{N}(S_i)} \right\}, \bigcup_{\xi_{\bar{N}(S_i)} \in \mathbb{F}_{\bar{N}(S_i)}} \left\{ \min_i \xi_{\bar{N}(S_i)} \right\} \right) \right\rangle.$$

Then, the aggregated values are bounded as follows:

$$N(S)^- \subseteq A_{MVRN}(N(S_1), \dots, N(S_n)) \subseteq N(S)^+.$$

$$N(S)^- \subseteq A_{MVRN}^w(N(S_1), \dots, N(S_n)) \subseteq N(S)^+.$$

Property 3 (Monotonicity): If $N(S_i) \leq N(S_i^*)$ for $i = 1, 2, \dots, n$, then:

$$A_{MVRN}(N(S_1), \dots, N(S_n)) \leq A_{MVRN}(N(S_1^*), \dots, N(S_n^*)),$$

And:

$$A_{MVRN}^w(N(S_1), \dots, N(S_n)) \leq A_{MVRN}^w(N(S_1^*), \dots, N(S_n^*)).$$

Proof: Since $N(S_i) \leq N(S_i^*)$ for all $i = 1, 2, \dots, n$, it follows that:

$$A_{MVRN}(N(S_1), N(S_2), \dots, N(S_n)) \leq A_{MVRN}(N(S_1), N(S_2), \dots, N(S_n^*)),$$

And similarly:

$$A_{MVRN}^w(N(S_1), N(S_2), \dots, N(S_n)) \leq A_{MVRN}^w(N(S_1), N(S_2), \dots, N(S_n^*)).$$

Definition 10: *Multi-Valued Rough Neutrosophic Geometric Mean Operator* (G_{MVRN})

Let $N(S_i) = (N(S_i), \bar{N}(S_i))$ for $(i = 1, 2, \dots, n)$ be a collection of MVRNNs. The Multi-Valued Rough Neutrosophic Geometric Mean Operator (G_{MVRN}) is then defined as:

$$G_{MVRN}(N(S_1), N(S_2), \dots, N(S_n)) = \left(\bigotimes_{i=1}^n (N(S_i))^{\frac{1}{n}}, \bigotimes_{i=1}^n (\bar{N}(S_i))^{\frac{1}{n}} \right)$$

Theorem 3: Let $N(S_i) = (N(S_i), \bar{N}(S_i))$ for $(i = 1, 2, \dots, n)$ be a collection of MVRNNs. The aggregated value obtained using the G_{MVRN} operator, defined as:

$$G_{MVRN}(N(S_1), N(S_2), \dots, N(S_n)) = \left(\bigotimes_{i=1}^n (N(S_i))^{\frac{1}{n}}, \bigotimes_{i=1}^n (\bar{N}(S_i))^{\frac{1}{n}} \right) \tag{7}$$

is also an MVRNN.

$$= \left\langle \left(\bigcup_{\gamma_{N(S_i)} \in T_{N(S_i)}} \left\{ \frac{2 \prod_{i=1}^n (\gamma_{N(S_i)})^{1/n}}{\prod_{i=1}^n (2 - \gamma_{N(S_i)})^{1/n} + \prod_{i=1}^n (\gamma_{N(S_i)})^{1/n}} \right\}, \bigcup_{\eta_{\bar{N}(S_i)} \in T_{\bar{N}(S_i)}} \left\{ \frac{\prod_{i=1}^n (1 + \eta_{\bar{N}(S_i)})^{1/n} - \prod_{i=1}^n (1 - \eta_{\bar{N}(S_i)})^{1/n}}{\prod_{i=1}^n (1 + \eta_{\bar{N}(S_i)})^{1/n} + \prod_{i=1}^n (1 - \eta_{\bar{N}(S_i)})^{1/n}} \right\}, \right. \right. \tag{8}$$

$$\left. \left. \left(\bigcup_{\xi_{N(S_i)} \in F_{N(S_i)}} \left\{ \frac{\prod_{i=1}^n (1 + \xi_{N(S_i)})^{1/n} - \prod_{i=1}^n (1 - \xi_{N(S_i)})^{1/n}}{\prod_{i=1}^n (1 + \xi_{N(S_i)})^{1/n} + \prod_{i=1}^n (1 - \xi_{N(S_i)})^{1/n}} \right\}, \left(\bigcup_{\gamma_{\bar{N}(S_i)} \in T_{\bar{N}(S_i)}} \left\{ \frac{2 \prod_{i=1}^n (\gamma_{\bar{N}(S_i)})^{1/n}}{\prod_{i=1}^n (2 - \gamma_{\bar{N}(S_i)})^{1/n} + \prod_{i=1}^n (\gamma_{\bar{N}(S_i)})^{1/n}} \right\}, \right. \right. \right.$$

$$\left. \left. \bigcup_{\eta_{\bar{N}(S_i)} \in F_{\bar{N}(S_i)}} \left\{ \frac{\prod_{i=1}^n (1 + \eta_{\bar{N}(S_i)})^{1/n} - \prod_{i=1}^n (1 - \eta_{\bar{N}(S_i)})^{1/n}}{\prod_{i=1}^n (1 + \eta_{\bar{N}(S_i)})^{1/n} + \prod_{i=1}^n (1 - \eta_{\bar{N}(S_i)})^{1/n}} \right\}, \bigcup_{\xi_{\bar{N}(S_i)} \in F_{\bar{N}(S_i)}} \left\{ \frac{\prod_{i=1}^n (1 + \xi_{\bar{N}(S_i)})^{1/n} - \prod_{i=1}^n (1 - \xi_{\bar{N}(S_i)})^{1/n}}{\prod_{i=1}^n (1 + \xi_{\bar{N}(S_i)})^{1/n} + \prod_{i=1}^n (1 - \xi_{\bar{N}(S_i)})^{1/n}} \right\} \right) \right\rangle.$$

Definition 11: *Weighted Multi-Valued Rough Neutrosophic Geometric Mean Operator* (G_{MVRN}^w)

Let $N(S_i) = (N(S_i), \bar{N}(S_i))$ for $i = 1, 2, \dots, n$ be a collection of MVRNNs, and let $w = (w_1, w_2, \dots, w_n)$ be the weight vector for $N(S_1), N(S_2), \dots, N(S_n)$, such that $w_i \in [0, 1]$ and $\sum_{i=1}^n w_i = 1$. The Weighted Multi-Valued Rough Neutrosophic Geometric Mean Operator (G_{MVRN}^w) is then defined as:

$$G_{MVRN}^w(N(S_1), N(S_2), \dots, N(S_n)) = \left(\bigotimes_{i=1}^n (N(S_i))^{w_i}, \bigotimes_{i=1}^n (\bar{N}(S_i))^{w_i} \right)$$

Theorem 4: Let $N(S_i) = (N(S_i), \bar{N}(S_i))$ for $(i = 1, 2, \dots, n)$ be a collection of MVRNNs, and let $w = (w_1, w_2, \dots, w_n)$ be the weight vector for $N(S_1), N(S_2), \dots, N(S_n)$, such that $w_i \in [0, 1]$ and $\sum_{i=1}^n w_i = 1$. The aggregated value obtained using the G_{MVRN}^w operator, defined as:

$$G_{MVRN}^w(N(S_1), N(S_2), \dots, N(S_n)) = \left(\bigotimes_{i=1}^n (N(S_i))^{w_i}, \bigotimes_{i=1}^n (\bar{N}(S_i))^{w_i} \right) \tag{9}$$

is also an MVRNN.

$$= \left\langle \left(\bigcup_{\gamma_{\underline{N}}(S_i) \in \mathbb{T}_{\underline{N}}(S_i)} \left\{ \frac{2 \prod_{i=1}^n (\gamma_{\underline{N}}(S_i))^{w_i}}{\prod_{i=1}^n (2 - \gamma_{\underline{N}}(S_i))^{w_i} + \prod_{i=1}^n (\gamma_{\underline{N}}(S_i))^{w_i}} \right\}, \bigcup_{\eta_{\underline{N}}(S_i) \in \mathbb{I}_{\underline{N}}(S_i)} \left\{ \frac{\prod_{i=1}^n (1 + \eta_{\underline{N}}(S_i))^{w_i} - \prod_{i=1}^n (1 - \eta_{\underline{N}}(S_i))^{w_i}}{\prod_{i=1}^n (1 + \eta_{\underline{N}}(S_i))^{w_i} + \prod_{i=1}^n (1 - \eta_{\underline{N}}(S_i))^{w_i}} \right\}, \right. \right. \\ \left. \left. \left(\bigcup_{\xi_{\underline{N}}(S_i) \in \mathbb{F}_{\underline{N}}(S_i)} \left\{ \frac{\prod_{i=1}^n (1 + \xi_{\underline{N}}(S_i))^{w_i} - \prod_{i=1}^n (1 - \xi_{\underline{N}}(S_i))^{w_i}}{\prod_{i=1}^n (1 + \xi_{\underline{N}}(S_i))^{w_i} + \prod_{i=1}^n (1 - \xi_{\underline{N}}(S_i))^{w_i}} \right\}, \left(\bigcup_{\gamma_{\overline{N}}(S_i) \in \mathbb{T}_{\overline{N}}(S_i)} \left\{ \frac{2 \prod_{i=1}^n (\gamma_{\overline{N}}(S_i))^{w_i}}{\prod_{i=1}^n (2 - \gamma_{\overline{N}}(S_i))^{w_i} + \prod_{i=1}^n (\gamma_{\overline{N}}(S_i))^{w_i}} \right\}, \right. \right. \right. \right. \\ \left. \left. \left. \bigcup_{\eta_{\overline{N}}(S_i) \in \mathbb{I}_{\overline{N}}(S_i)} \left\{ \frac{\prod_{i=1}^n (1 + \eta_{\overline{N}}(S_i))^{w_i} - \prod_{i=1}^n (1 - \eta_{\overline{N}}(S_i))^{w_i}}{\prod_{i=1}^n (1 + \eta_{\overline{N}}(S_i))^{w_i} + \prod_{i=1}^n (1 - \eta_{\overline{N}}(S_i))^{w_i}} \right\}, \bigcup_{\xi_{\overline{N}}(S_i) \in \mathbb{F}_{\overline{N}}(S_i)} \left\{ \frac{\prod_{i=1}^n (1 + \xi_{\overline{N}}(S_i))^{w_i} - \prod_{i=1}^n (1 - \xi_{\overline{N}}(S_i))^{w_i}}{\prod_{i=1}^n (1 + \xi_{\overline{N}}(S_i))^{w_i} + \prod_{i=1}^n (1 - \xi_{\overline{N}}(S_i))^{w_i}} \right\} \right) \right) \right. \right. \right. \right. \quad (10)$$

Proof: Theorem 4 can be proved using mathematical induction.

Similarly, the G_{MVRN} operator satisfies the following properties.

Property 4 (Idempotency Law): If all MVRNNs are identical, i.e., $N(S_i) = N(S)$ for $i = 1, 2, \dots, n$, then:

$$G_{MVRN}(N(S_1), N(S_2), \dots, N(S_n)) = N(S)$$

and

$$G_{MVRN}^w(N(S_1), N(S_2), \dots, N(S_n)) = N(S).$$

Proof: For $N(S_i) = N(S)$, by definition of G_{MVRN} operator:

$$G_{MVRN}(N(S_1), \dots, N(S_n)) = \left(\bigotimes_{i=1}^n (N(S))^{w_i}, \bigotimes_{i=1}^n (\overline{N}(S))^{w_i} \right) = (N(S), \overline{N}(S)) = N(S).$$

For G_{MVRN}^w operator, given $\sum_{i=1}^n w_i = 1$:

$$G_{MVRN}^w(N(S_1), \dots, N(S_n)) = \left(\bigotimes_{i=1}^n (N(S))^{w_i}, \bigotimes_{i=1}^n (\overline{N}(S))^{w_i} \right) = (N(S), \overline{N}(S)) = N(S).$$

This holds because $\bigotimes_{i=1}^n X^{w_i} = X$ when $\sum w_i = 1$ for any MVRNN X (based on the definition of weighted aggregation and scalar multiplication).

Property 5 (Boundedness): Both the G_{MVRN} and G_{MVRN}^w Operators are bounded. That is, for a given set of MVRNNs $N(S_i)$ ($i = 1, 2, \dots, n$), the aggregated values satisfy:

$$N(S)^- \leq G_{MVRN}(N(S_1), \dots, N(S_n)) \leq N(S)^+$$

and

$$N(S)^- \leq G_{MVRN}^w(N(S_1), \dots, N(S_n)) \leq N(S)^+.$$

Here, $N(S)^-$ and $N(S)^+$ are the lower and upper bounds defined previously (refer to Property 2).

Proof: The proof for boundedness follows from the definitions of the geometric aggregation operators and the properties of Einstein operators, similar to Property 2.

Property 6 (Monotonicity): If $N(S_i) \leq N(S_i^*)$ for $i = 1, 2, \dots, n$, then:

$$G_{MVRN}(N(S_1), \dots, N(S_n)) \leq G_{MVRN}(N(S_1^*), \dots, N(S_n^*)),$$

And:

$$G_{MVRN}^w(N(S_1), \dots, N(S_n)) \leq G_{MVRN}^w(N(S_1^*), \dots, N(S_n^*)).$$

Proof: Since $N(S_i) \leq N(S_i^*)$ for all $i = 1, 2, \dots, n$, it follows that:

$$G_{MVRN}(N(S_1), N(S_2), \dots, N(S_n)) \leq G_{MVRN}(N(S_1), N(S_2), \dots, N(S_n^*)),$$

And similarly: $G_{MVRN}^w(N(S_1), N(S_2), \dots, N(S_n)) \leq G_{MVRN}^w(N(S_1), N(S_2), \dots, N(S_n^*)).$

Definition 12: *Score function and accuracy function*

Let $\mathbb{N}(\mathbb{S}) = \langle (\mathbb{T}_{\mathbb{N}(\mathbb{S})}, \mathbb{I}_{\mathbb{N}(\mathbb{S})}, \mathbb{F}_{\mathbb{N}(\mathbb{S})}), (\mathbb{T}_{\bar{\mathbb{N}}(\mathbb{S})}, \mathbb{I}_{\bar{\mathbb{N}}(\mathbb{S})}, \mathbb{F}_{\bar{\mathbb{N}}(\mathbb{S})}) \rangle$ be an MVRNN. The associated score function s for $\mathbb{N}(\mathbb{S})$ can be defined as:

$$s(\mathbb{N}(\mathbb{S})) = \frac{1}{4} \left(3 + \frac{1}{l_{\mathbb{T}}} \sum_{k=1}^{l_{\mathbb{T}}} \mathbb{T}_{\mathbb{N}(\mathbb{S})k} + \frac{1}{l_{\bar{\mathbb{T}}}} \sum_{k=1}^{l_{\bar{\mathbb{T}}}} \mathbb{T}_{\bar{\mathbb{N}}(\mathbb{S})k} - \frac{2}{l_{\mathbb{I}}} \sum_{g=1}^{l_{\mathbb{I}}} \mathbb{I}_{\mathbb{N}(\mathbb{S})g} - \frac{2}{l_{\bar{\mathbb{I}}}} \sum_{g=1}^{l_{\bar{\mathbb{I}}}} \mathbb{I}_{\bar{\mathbb{N}}(\mathbb{S})g} - \frac{1}{l_{\mathbb{F}}} \sum_{r=1}^{l_{\mathbb{F}}} \mathbb{F}_{\mathbb{N}(\mathbb{S})r} - \frac{1}{l_{\bar{\mathbb{F}}}} \sum_{r=1}^{l_{\bar{\mathbb{F}}}} \mathbb{F}_{\bar{\mathbb{N}}(\mathbb{S})r} \right) \quad (11)$$

The accuracy function a for $\mathbb{N}(\mathbb{S})$ can then be defined as:

$$a(\mathbb{N}(\mathbb{S})) = \frac{1}{4} \left(3 + \frac{1}{l_{\mathbb{T}}} \sum_{k=1}^{l_{\mathbb{T}}} \mathbb{T}_{\mathbb{N}(\mathbb{S})k} + \frac{1}{l_{\bar{\mathbb{T}}}} \sum_{k=1}^{l_{\bar{\mathbb{T}}}} \mathbb{T}_{\bar{\mathbb{N}}(\mathbb{S})k} - \frac{2}{l_{\mathbb{I}}l_{\mathbb{T}}} \sum_{g=1}^{l_{\mathbb{I}}} \sum_{k=1}^{l_{\mathbb{T}}} \mathbb{I}_{\mathbb{N}(\mathbb{S})g}(1 - \mathbb{T}_{\mathbb{N}(\mathbb{S})k}) - \frac{2}{l_{\bar{\mathbb{I}}}l_{\bar{\mathbb{T}}}} \sum_{g=1}^{l_{\bar{\mathbb{I}}}} \sum_{k=1}^{l_{\bar{\mathbb{T}}}} \mathbb{I}_{\bar{\mathbb{N}}(\mathbb{S})g}(1 - \mathbb{T}_{\bar{\mathbb{N}}(\mathbb{S})k}) \right. \\ \left. - \frac{1}{l_{\mathbb{F}}l_{\mathbb{I}}} \sum_{r=1}^{l_{\mathbb{F}}} \sum_{g=1}^{l_{\mathbb{I}}} \mathbb{F}_{\mathbb{N}(\mathbb{S})r}(1 - \mathbb{I}_{\mathbb{N}(\mathbb{S})g}) - \frac{1}{l_{\bar{\mathbb{F}}}l_{\bar{\mathbb{I}}}} \sum_{r=1}^{l_{\bar{\mathbb{F}}}} \sum_{g=1}^{l_{\bar{\mathbb{I}}}} \mathbb{F}_{\bar{\mathbb{N}}(\mathbb{S})r}(1 - \mathbb{I}_{\bar{\mathbb{N}}(\mathbb{S})g}) \right) \quad (12)$$

Proposed MCDM methods

In real-world situations, choosing the best option from a set of possibilities often involves complex criteria and inherent uncertainties. Traditional approaches may oversimplify these complexities, leading to suboptimal decisions. The Multi-Valued Rough Neutrosophic Arithmetic Mean Operator (\mathbb{A}_{MVRN}), the Weighted Multi-Valued Rough Neutrosophic Arithmetic Mean Operator (\mathbb{A}_{MVRN}^w), the Multi-Valued Rough Neutrosophic Geometric Mean Operator (\mathbb{G}_{MVRN}), and the Weighted Multi-Valued Rough Neutrosophic Geometric Mean Operator (\mathbb{G}_{MVRN}^w) are four advanced multi-criteria decision-making methods based on MVRNNs. These methods provide a reliable way to evaluate options under uncertainty.

The process includes forming a decision matrix, aggregating values, computing scores, and ranking alternatives, with differences in weights and aggregation operators. In this context, let the set of criteria be represented by $\mathbb{C} = \{\mathbb{C}_1, \mathbb{C}_2, \dots, \mathbb{C}_n\}$ and the set of alternatives is represented by $\mathbb{A} = \{\mathbb{A}_1, \mathbb{A}_2, \dots, \mathbb{A}_m\}$. Decision-makers assess each alternative \mathbb{A}_j with respect to each criterion \mathbb{C}_i , utilizing MVRNNs for evaluation. Tables 1 and 2 show the MVRNN-based relationship and the corresponding decision matrix, respectively. MVRNNs were used to create the decision matrix, which has the following structure:

The suggested MCDM method’s procedural flow is shown in a unified framework in Fig. 1, which highlights the similarities and differences between the four aggregation operators.

Table 1. The relation between alternatives and criteria in terms of MVRNNs.

$DM[\mathbb{A} \mathbb{C}_1, \mathbb{C}_2, \mathbb{C}_3, \dots, \mathbb{C}_n] =$	\mathbb{C}_1	\mathbb{C}_2	\dots	\mathbb{C}_n
\mathbb{A}_1	$\langle \mathbb{N}_{11}, \bar{\mathbb{N}}_{11} \rangle$	$\langle \mathbb{N}_{12}, \bar{\mathbb{N}}_{12} \rangle$	\dots	$\langle \mathbb{N}_{1n}, \bar{\mathbb{N}}_{1n} \rangle$
\mathbb{A}_2	$\langle \mathbb{N}_{21}, \bar{\mathbb{N}}_{21} \rangle$	$\langle \mathbb{N}_{22}, \bar{\mathbb{N}}_{22} \rangle$	\dots	$\langle \mathbb{N}_{2n}, \bar{\mathbb{N}}_{2n} \rangle$
\mathbb{A}_m	$\langle \mathbb{N}_{m1}, \bar{\mathbb{N}}_{m1} \rangle$	$\langle \mathbb{N}_{m2}, \bar{\mathbb{N}}_{m2} \rangle$	\dots	$\langle \mathbb{N}_{mn}, \bar{\mathbb{N}}_{mn} \rangle$

Method 1: Multi-valued rough neutrosophic arithmetic mean operator

This method uses the MVRNAMO to aggregate the evaluation values. The procedure is:

- Construct a Decision Matrix:** Define the relationship between alternatives \mathbb{A}_j and criteria \mathbb{C}_i using an MVRNN-based decision matrix, see Table 1.
- Aggregate Evaluations:** Apply MVRNAMO (using Eq. (3) and Eq. (4)) to compute aggregated total values for each alternative.
- Compute Score and Accuracy Functions:** Use Eq. (11) and Eq. (12) to calculate the score and accuracy values for the aggregated alternative.
- Rank Alternatives:** Sort alternatives by score values in decreasing order. Accuracy values are used to break ties if needed.

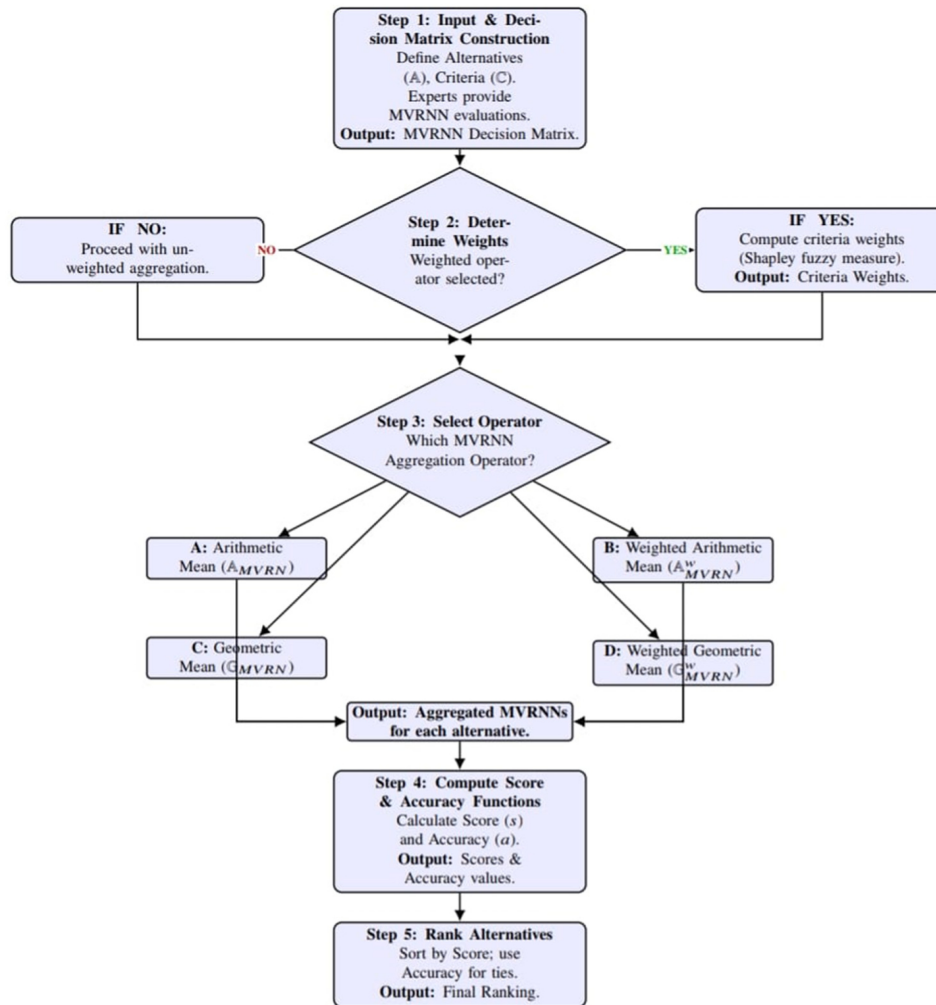


Fig. 1. Unified framework for multi-criteria decision-making using MVRN aggregation operators.

Method 2: Weighted multi-valued rough neutrosophic arithmetic mean operator

This method extends method 1 by incorporating criteria. The procedure is:

1. **Construct the Decision Matrix:** The decision matrix is the same as method 1, representing evaluations as MVRNNs Table 1.
2. **Determine Criteria Weights:** Calculate weights using an appropriate approach, such as the Shapley fuzzy measure (e.g., as defined in Eqs. (1) and (2)).
3. **Compute Weighted Aggregation:** Using the Weighted Multi-Valued Rough Neutrosophic Arithmetic Mean Operator Eqs. (5) and (6) to obtain weighted aggregated values for each alternative.
4. **Compute Score and Accuracy Functions:** Use Eqs. (11) and (12) to calculate the score and accuracy values for the aggregated alternative.
5. **Rank Alternatives:** Sort alternatives by score values in decreasing order. Accuracy values are used to break ties if needed.

Method 3: Multi-valued rough neutrosophic geometric mean operator

This method uses the MVRNGMO to aggregate the evaluation values. The procedure is:

1. **Construct the Decision Matrix:** The decision matrix is constructed using MVRNNs, as described in previous methods Table 1.

2. **Aggregate Evaluations:** Apply MVRNGMO (using Eqs. (7) and (8)) to compute aggregated total values for each alternative.
3. **Compute Score and Accuracy Functions:** Use Eqs. (11) and (12) to calculate the score and accuracy values for the aggregated alternative.
4. **Rank Alternatives:** Sort alternatives by score values in decreasing order. Accuracy values are used to break ties if needed.

Method 4: Weighted multi-valued rough neutrosophic geometric mean operator

This method combines the geometric mean aggregation with criteria weights, using the WMVRNGMO.

1. **Construct the Decision Matrix:** The decision matrix is the same as method 1, representing evaluations as MVRNNs Table 1.
2. **Determine Criteria Weights:** Calculate weights using an appropriate approach, such as the Shapley fuzzy measure (e.g., as defined in Eqs. (1) and (2)).
3. **Compute Weighted Aggregation:** Using the Weighted Multi-Valued Rough Neutrosophic Geometric Mean Operator Eqs. (9) and (10) to obtain weighted aggregated values for each alternative.
4. **Compute Score and Accuracy Functions:** Use Eqs. (11) and (12) to calculate the score and accuracy values for the aggregated alternative.
5. **Rank Alternatives:** Sort alternatives by score values in decreasing order. Accuracy values are used to break ties if needed.

Numerical example: Selecting the best hospital for a patient

In real-world decision-making, uncertainty and vagueness often make it difficult to choose the best option. This is especially true in critical situations like hospital selection, where both time and accuracy are vital. Traditional decision-making methods may struggle to deal with such complexity and conflicting criteria.

This study proposes an MVRNNs-based MCDM using aggregation operators and Shapley weights for accurate decision-making under uncertainty.

Hospital selection scenario

In critical situations, a family must quickly choose the most suitable hospital. The decision is based on 3 criteria:

- C_1 : **Doctor Availability**
- C_2 : **Waiting Time**
- C_3 : **Treatment Success Rate**

Four alternatives are considered:

- A_1 : **Private Hospital**
- A_2 : **Government Hospital**
- A_3 : **Multi-Speciality Hospital**
- A_4 : **Charity Hospital**

Expert evaluations are analyzed using MVRNN-based aggregation to handle uncertainty and rank the hospitals.

Table 2. The decision matrix based on MVRNNs for hospital selection.

$DM[A C_1, C_2, C_3]$	C_1	C_2	C_3
A_1	$\langle\langle\{0.7\}, \{0.3\}, \{0, 0.2\}\rangle\rangle$ $\langle\langle\{0.9, 1\}, \{0.1, 0.2\}, \{0\}\rangle\rangle$	$\langle\langle\{0.4\}, \{0.6\}, \{0.5\}\rangle\rangle$ $\langle\langle\{0.7\}, \{0.3\}, \{0, 0.2\}\rangle\rangle$	$\langle\langle\{0.5, 0.8\}, \{0.2, 0.3\}, \{0.1\}\rangle\rangle$ $\langle\langle\{0.6, 0.9\}, \{0.2, 0.4\}, \{0.2\}\rangle\rangle$
A_2	$\langle\langle\{0.4\}, \{0.6\}, \{0.3\}\rangle\rangle$ $\langle\langle\{0.8, 1\}, \{0.1, 0.2\}, \{0\}\rangle\rangle$	$\langle\langle\{0.7\}, \{0.3\}, \{0.2\}\rangle\rangle$ $\langle\langle\{0.8, 0.9\}, \{0.1\}, \{0\}\rangle\rangle$	$\langle\langle\{0.3\}, \{0.7\}, \{0.8\}\rangle\rangle$ $\langle\langle\{0.7\}, \{0.3\}, \{0.1\}\rangle\rangle$
A_3	$\langle\langle\{0.9, 1\}, \{0.2\}, \{0\}\rangle\rangle$ $\langle\langle\{0.8, 1\}, \{0, 0.2\}, \{0\}\rangle\rangle$	$\langle\langle\{0.5, 0.7\}, \{0.2, 0.3\}, \{0, 0.1\}\rangle\rangle$ $\langle\langle\{.6\}, \{0, 0.4\}, \{0, 0.2\}\rangle\rangle$	$\langle\langle\{0.4\}, \{0.6\}, \{0, 0.2\}\rangle\rangle$ $\langle\langle\{0.6, 0.8\}, \{0, 0.2\}, \{0.3\}\rangle\rangle$
A_4	$\langle\langle\{0.6, 0.7\}, \{0.3\}, \{0.1\}\rangle\rangle$ $\langle\langle\{0.8, 1\}, \{0.2\}, \{0\}\rangle\rangle$	$\langle\langle\{0.3\}, \{0.7\}, \{0.8, 1\}\rangle\rangle$ $\langle\langle\{0.6, 0.7\}, \{0.2, 0.3\}, \{0.1\}\rangle\rangle$	$\langle\langle\{0, 0.2\}, \{0.8\}, \{0.9\}\rangle\rangle$ $\langle\langle\{0.5, 0.8\}, \{0.2\}, \{0.3\}\rangle\rangle$

Proposed MCDM methodology application

This section applies the proposed MCDM framework to the hospital selection problem using four MVRNN aggregations. Each operator processes the decision matrix to produce a reliable ranking. The procedure for all operators follows a similar path, including aggregation, score calculation, and ranking.

The individual fuzzy measures for the criteria (i.e., $\mu(e_1) = 0.4$, $\mu(e_2) = 0.25$, $\mu(e_3) = 0.45$) were initially determined using a pairwise comparison method based on expert judgments. Subsequently, these measures were utilized to compute the Shapley fuzzy measures, as detailed in the following steps.

Fuzzy measure of attributes and criteria weights

The individual fuzzy measures for the criteria are given as:

$$\mu(e_1) = 0.4, \mu(e_2) = 0.25, \mu(e_3) = 0.45$$

The value of λ is calculated using the following equation:

$$\lambda + 1 = (1 + 0.4\lambda)(1 + 0.25\lambda)(1 + 0.45\lambda)$$

Solving this equation gives:

$$\lambda = -0.2622$$

The fuzzy measure of attributes is obtained:

$$\mu(e_1, e_2) = \frac{1}{-0.2622}((1 - 0.2622 \cdot (0.4))(1 - 0.2622 \cdot (0.25)) - 1) = 0.6238$$

Similarly, for other combinations:

$$\mu(e_1, e_3) = 0.8028, \mu(e_2, e_3) = 0.6705, \mu(e_1, e_2, e_3) = 1$$

After that, the Shapley fuzzy measures (SFM) can be obtained from Eq. (2) as follows:

$$\begin{aligned} w(\mu, \alpha) &= \frac{(3-0-1)!}{3!} (\mu(e_1) - \mu(\phi)) + \frac{(3-1-1)!}{3!} (\mu(e_1, e_2) - \mu(e_2)) + \frac{(3-1-1)!}{3!} (\mu(e_1, e_3) - \mu(e_3)) \\ &\quad + \frac{(3-2-1)!}{3!} (\mu(e_1, e_2, e_3) - \mu(e_2, e_3)) \\ &= \frac{1}{3}(0.4 - 0) + \frac{1}{6}(0.6238 - 0.25) + \frac{1}{6}(0.8028 - 0.45) + \frac{1}{3}(1 - 0.6705) = 0.364 \end{aligned}$$

Similarly,

$$w_2(\mu, \alpha) = 0.223, w_3(\mu, \alpha) = 0.413$$

Thus, the final criteria weights are:

$$w_1 = 0.364, w_2 = 0.223, w_3 = 0.413.$$

Method 1: Multi-valued rough neutrosophic arithmetic mean operator

This method applies the MVRNAMO to aggregate the initial MVRNN evaluations.

Step 1: Construct the MVRNN-based decision matrix.

The decision matrix, which defines the relationship between alternatives and criteria, is established using MVRNNs as presented in Table 2.

Step 2: Aggregate the decision matrix using the MVRN Arithmetic Mean Operator. We apply the aggregation operator to each alternative. For alternative \mathbb{A}_1 :

Let $\underline{N}_{11} = \langle (\{0.7\}, \{0.3\}, \{0, 0.2\}), (\{0.9, 1\}, \{0.1, 0.2\}, \{0\}) \rangle$

Let $\underline{N}_{12} = \langle (\{0.4\}, \{0.6\}, \{0.5\}), (\{0.7\}, \{0.3\}, \{0, 0.2\}) \rangle$

Let $\underline{N}_{13} = \langle (\{0.5, 0.8\}, \{0.2, 0.3\}, \{0.1\}), (\{0.6, 0.9\}, \{0.2, 0.4\}, \{0.2\}) \rangle$

The aggregated MVRNN for $\mathbb{A}_{MVRN}[\mathbb{A}_1 | \mathbb{C}_1, \mathbb{C}_2, \mathbb{C}_3]$ is calculated as:

$$\begin{aligned} \mathbb{A}_{MVRN}[\mathbb{A}_1 | \mathbb{C}_1, \mathbb{C}_2, \mathbb{C}_3] &= \langle \frac{1}{3}(\underline{N}_{11} \oplus \underline{N}_{12} \oplus \underline{N}_{13}), \frac{1}{3}(\bar{N}_{11} \oplus \bar{N}_{12} \oplus \bar{N}_{13}) \rangle \\ &= \left\langle \frac{1}{3}((\{0.7\}, \{0.3\}, \{0, 0.2\}) \oplus (\{0.4\}, \{0.6\}, \{0.5\}) \oplus (\{0.5, 0.8\}, \{0.2, 0.3\}, \{0.1\})), \right. \\ &\quad \left. \frac{1}{3}((\{0.9, 1\}, \{0.1, 0.2\}, \{0\}) \oplus (\{0.7\}, \{0.3\}, \{0, 0.2\}) \oplus (\{0.6, 0.9\}, \{0.2, 0.4\}, \{0.2\})) \right\rangle \\ &= \langle (\{0.5465, 0.6621\}, \{0.3379, 0.3884\}, \{0, 0.2221\}), (\{0.7662, 1\}, \{0.1836, 0.2904\}, \{0\}) \rangle. \end{aligned}$$

For alternative \mathbb{A}_2 :

Let $\underline{N}_{21} = \langle (\{0.4\}, \{0.6\}, \{0.3\}), (\{0.8, 1\}, \{0.1, 0.2\}, \{0\}) \rangle$

Let $\underline{N}_{22} = \langle (\{0.7\}, \{0.3\}, \{0.2\}), (\{0.8, 0.9\}, \{0.1\}, \{0\}) \rangle$

Let $\underline{N}_{23} = \langle (\{0.3\}, \{0.7\}, \{0.8, 1\}), (\{0.7\}, \{0.3\}, \{0.1\}) \rangle$

The aggregated MVRNN for $\mathbb{A}_{MVRN}[\mathbb{A}_2 | \mathbb{C}_1, \mathbb{C}_2, \mathbb{C}_3]$ is calculated as:

$$\begin{aligned} \mathbb{A}_{MVRN}[\mathbb{A}_2 | \mathbb{C}_1, \mathbb{C}_2, \mathbb{C}_3] &= \langle \frac{1}{3}(\underline{N}_{21} \oplus \underline{N}_{22} \oplus \underline{N}_{23}), \frac{1}{3}(\bar{N}_{21} \oplus \bar{N}_{22} \oplus \bar{N}_{23}) \rangle \\ &= \left\langle \frac{1}{3}((\{0.4\}, \{0.6\}, \{0.3\}) \oplus (\{0.7\}, \{0.3\}, \{0.2\}) \oplus (\{0.3\}, \{0.7\}, \{0.8, 1\})), \right. \\ &\quad \left. \frac{1}{3}((\{0.8, 1\}, \{0.1, 0.2\}, \{0\}) \oplus (\{0.8, 0.9\}, \{0.1\}, \{0\}) \oplus (\{0.7\}, \{0.3\}, \{0.1\})) \right\rangle \\ &= \langle (\{0.4881\}, \{0.5120\}, \{0.3813, 0.4248\}), (\{0.7705, 1\}, \{0.1460, 0.1678\}, \{0\}) \rangle. \end{aligned}$$

For alternative \mathbb{A}_3 :

Let $\underline{N}_{31} = \langle (\{0.9, 1\}, \{0.2\}, \{0\}), (\{0.8, 1\}, \{0, 0.2\}, \{0\}) \rangle$

Let $\underline{N}_{32} = \langle (\{0.5, 0.7\}, \{0.2, 0.3\}, \{0, 0.1\}), (\{0.6\}, \{0, 0.4\}, \{0, 0.2\}) \rangle$

Let $\underline{N}_{33} = \langle (\{0.4\}, \{0.6\}, \{0, 0.2\}), (\{0.6, 0.8\}, \{0, 0.2\}, \{0, 0.3\}) \rangle$

The aggregated MVRNN for $\mathbb{A}_{MVRN}[\mathbb{A}_3 | \mathbb{C}_1, \mathbb{C}_2, \mathbb{C}_3]$ is calculated as:

$$\begin{aligned} \mathbb{A}_{MVRN}[\mathbb{A}_3 | \mathbb{C}_1, \mathbb{C}_2, \mathbb{C}_3] &= \langle \frac{1}{3}(\underline{N}_{31} \oplus \underline{N}_{32} \oplus \underline{N}_{33}), \frac{1}{3}(\bar{N}_{31} \oplus \bar{N}_{32} \oplus \bar{N}_{33}) \rangle \\ &= \left\langle \frac{1}{3}((\{0.9, 1\}, \{0.2\}, \{0\}) \oplus (\{0.5, 0.7\}, \{0.2, 0.3\}, \{0, 0.1\}) \oplus (\{0.4\}, \{0.6\}, \{0, 0.2\})), \right. \\ &\quad \left. \frac{1}{3}((\{0.8, 1\}, \{0, 0.2\}, \{0\}) \oplus (\{0.6\}, \{0, 0.4\}, \{0, 0.2\}) \oplus (\{0.6, 0.8\}, \{0, 0.2\}, \{0, 0.3\})) \right\rangle \\ &= \langle (\{0.6724, 1\}, \{0.2968, 0.3379\}, \{0\}), (\{0.6796, 1\}, \{0, 0.2542\}, \{0\}) \rangle. \end{aligned}$$

For alternative \mathbb{A}_4 :

Let $\underline{N}_{41} = \langle (\{0.6, 0.7\}, \{0.3\}, \{0.1\}), (\{0.8, 1\}, \{0.2\}, \{0\}) \rangle$

Let $\underline{N}_{42} = \langle (\{0.3\}, \{0.7\}, \{0.8, 1\}), (\{0.6, 0.7\}, \{0.2, 0.3\}, \{0.1\}) \rangle$

Let $\underline{N}_{43} = \langle (\{0, 0.2\}, \{0.8\}, \{0.9\}), (\{0.5, 0.8\}, \{0.2\}, \{0.3\}) \rangle$

The aggregated MVRNN for $\mathbb{A}_{MVRN}[\mathbb{A}_4 | \mathbb{C}_1, \mathbb{C}_2, \mathbb{C}_3]$ is calculated as:

$$\begin{aligned} \mathbb{A}_{MVRN}[\mathbb{A}_4 | \mathbb{C}_1, \mathbb{C}_2, \mathbb{C}_3] &= \langle \frac{1}{3}(\underline{N}_{41} \oplus \underline{N}_{42} \oplus \underline{N}_{43}), \frac{1}{3}(\bar{N}_{41} \oplus \bar{N}_{42} \oplus \bar{N}_{43}) \rangle \\ &= \left\langle \frac{1}{3}((\{0.6, 0.7\}, \{0.3\}, \{0.1\}) \oplus (\{0.3\}, \{0.7\}, \{0.8, 1\}) \oplus (\{0, 0.2\}, \{0.8\}, \{0.9\})), \right. \\ &\quad \left. \frac{1}{3}((\{0.8, 1\}, \{0.2\}, \{0\}) \oplus (\{0.6, 0.7\}, \{0.2, 0.3\}, \{0.1\}) \oplus (\{0.5, 0.8\}, \{0.2\}, \{0.3\})) \right\rangle \\ &= \langle (\{0.3223, 0.4300\}, \{0.570\}, \{0.4688, 0.5191\}), (\{0.6529, 1\}, \{0.2, 0.2295\}, \{0\}) \rangle. \end{aligned}$$

Step 3: Compute score and accuracy metrics. Using Eqs. (11) and (12), we calculate each alternative’s score (s) and accuracy (a) functions for the aggregated MVRNNs:

$$s(\mathbb{A}_1) = 0.7940, \quad s(\mathbb{A}_2) = 0.6581, \quad s(\mathbb{A}_3) = 0.9468, \quad s(\mathbb{A}_4) = 0.4274.$$

Since all the score values (SV) are distinct, in this case, there is no need to compute the accuracy values (AV).

Step 4: Rank alternatives.

The alternatives are ranked based on their scores in descending order as follows:

$$\mathbb{A}_3 > \mathbb{A}_1 > \mathbb{A}_2 > \mathbb{A}_4.$$

Therefore, \mathbb{A}_3 (Multi-Speciality Hospital) is identified as the best choice.

Method 2: Weighted multi-valued rough neutrosophic arithmetic mean operator

This method extends Method 1 by incorporating criteria weights to reflect their relative importance, using the WMVRNAMO.

Step 1: Construct the decision matrix.

The decision matrix is constructed similarly to Method 1, representing evaluations as MVRNNs Table 2.

Step 2: Determine the criteria weights.

The criteria weights (w_1, w_2, w_3) are determined using the Shapley fuzzy measure, as detailed in the “Fuzzy Measure of Attributes and Criteria Weights” subsection. The weights assigned to the criteria are as follows:

$$w_1 = 0.364, \quad w_2 = 0.223, \quad w_3 = 0.413.$$

Step 3: Calculation of weighted aggregation values.

Using Eq. (6), weighted aggregation values are computed for each alternative, showing their MVRNNs and corresponding weights.

For alternative \mathbb{A}_1 :

$$\text{Let } \mathbb{N}_{11} = \langle \langle \{0.7\}, \{0.3\}, \{0, 0.2\} \rangle, \langle \{0.9, 1\}, \{0.1, 0.2\}, \{0\} \rangle \rangle$$

$$\text{Let } \mathbb{N}_{12} = \langle \langle \{0.4\}, \{0.6\}, \{0.5\} \rangle, \langle \{0.7\}, \{0.3\}, \{0, 0.2\} \rangle \rangle$$

$$\text{Let } \mathbb{N}_{13} = \langle \langle \{0.5, 0.8\}, \{0.2, 0.3\}, \{0.1\} \rangle, \langle \{0.6, 0.9\}, \{0.2, 0.4\}, \{0.2\} \rangle \rangle$$

The aggregated MVRNN for $\mathbb{A}^w_{MVRN}[\mathbb{A}_1 | \mathbb{C}_1, \mathbb{C}_2, \mathbb{C}_3]$ is calculated as:

$$\begin{aligned} \mathbb{A}^w_{MVRN}[\mathbb{A}_1 | \mathbb{C}_1, \mathbb{C}_2, \mathbb{C}_3] &= \langle w_1 \mathbb{N}_{11} \oplus w_2 \mathbb{N}_{12} \oplus w_3 \mathbb{N}_{13}, \quad w_1 \bar{\mathbb{N}}_{11} \oplus w_2 \bar{\mathbb{N}}_{12} \oplus w_3 \bar{\mathbb{N}}_{13} \rangle \\ &= \left\langle \begin{aligned} &\langle (0.364(\{0.7\}, \{0.3\}, \{0, 0.2\}) \oplus 0.223(\{0.4\}, \{0.6\}, \{0.5\}) \oplus 0.413(\{0.5, 0.8\}, \{0.2, 0.3\}, \{0.1\})), \\ &(0.364(\{0.9, 1\}, \{0.1, 0.2\}, \{0\}) \oplus 0.223(\{0.7\}, \{0.3\}, \{0, 0.2\}) \oplus 0.413(\{0.6, 0.9\}, \{0.2, 0.4\}, \{0.2\})) \rangle \end{aligned} \right\rangle \\ &= \langle \langle \{0.5629, 0.6982\}, \{0.3017, 0.3540\}, \{0, 0.1888\} \rangle, \langle \{0.7680, 1\}, \{0.1716, 0.2320\}, \{0\} \rangle \rangle. \end{aligned}$$

For alternative \mathbb{A}_2 :

$$\text{Let } \mathbb{N}_{21} = \langle \langle \{0.4\}, \{0.6\}, \{0.3\} \rangle, \langle \{0.8, 1\}, \{0.1, 0.2\}, \{0\} \rangle \rangle$$

$$\text{Let } \mathbb{N}_{22} = \langle \langle \{0.7\}, \{0.3\}, \{0.2\} \rangle, \langle \{0.8, 0.9\}, \{0.1\}, \{0\} \rangle \rangle$$

$$\text{Let } \mathbb{N}_{23} = \langle \langle \{0.3\}, \{0.7\}, \{0.8, 1\} \rangle, \langle \{0.7\}, \{0.3\}, \{0.1\} \rangle \rangle$$

The aggregated MVRNN for $\mathbb{A}^w_{MVRN}[\mathbb{A}_2 | \mathbb{C}_1, \mathbb{C}_2, \mathbb{C}_3]$ is calculated as:

$$\begin{aligned} \mathbb{A}^w_{MVRN}[\mathbb{A}_2 | \mathbb{C}_1, \mathbb{C}_2, \mathbb{C}_3] &= \langle w_1 \mathbb{N}_{21} \oplus w_2 \mathbb{N}_{22} \oplus w_3 \mathbb{N}_{23}, \quad w_1 \bar{\mathbb{N}}_{21} \oplus w_2 \bar{\mathbb{N}}_{22} \oplus w_3 \bar{\mathbb{N}}_{23} \rangle \\ &= \left\langle \begin{aligned} &\langle (0.364(\{0.4\}, \{0.6\}, \{0.3\}) \oplus 0.223(\{0.7\}, \{0.3\}, \{0.2\}) \oplus 0.413(\{0.3\}, \{0.7\}, \{0.8, 1\})), \\ &(0.364(\{0.8, 1\}, \{0.1, 0.2\}, \{0\}) \oplus 0.223(\{0.8, 0.9\}, \{0.1\}, \{0\}) \oplus 0.413(\{0.7\}, \{0.3\}, \{0.1\})) \rangle \end{aligned} \right\rangle \\ &= \langle \langle \{0.4426\}, \{0.5574\}, \{0.4321, 0.4915\} \rangle, \langle \{0.7628, 1\}, \{0.1596, 0.2045\}, \{0\} \rangle \rangle. \end{aligned}$$

For alternative \mathbb{A}_3 :

Let $\mathbb{N}_{31} = \langle \langle \{0.9, 1\}, \{0.2\}, \{0\} \rangle, \langle \{0.8, 1\}, \{0, 0.2\}, \{0\} \rangle \rangle$

Let $\mathbb{N}_{32} = \langle \langle \{0.5, 0.7\}, \{0.2, 0.3\}, \{0, 0.1\} \rangle, \langle \{.6\}, \{0, 0.4\}, \{0, 0.2\} \rangle \rangle$

Let $\mathbb{N}_{33} = \langle \langle \{0.4\}, \{0.6\}, \{0, 0.2\} \rangle, \langle \{0.6, 0.8\}, \{0, 0.2\}, \{0, 0.3\} \rangle \rangle$

The aggregated MVRNN for $\mathbb{A}^w_{MVRN}[\mathbb{A}_3|\mathbb{C}_1, \mathbb{C}_2, \mathbb{C}_3]$ is calculated as:

$$\begin{aligned} \mathbb{A}^w_{MVRN}[\mathbb{A}_3|\mathbb{C}_1, \mathbb{C}_2, \mathbb{C}_3] &= \langle w_1\mathbb{N}_{31} \oplus w_2\mathbb{N}_{32} \oplus w_3\mathbb{N}_{33}, w_1\bar{\mathbb{N}}_{31} \oplus w_2\bar{\mathbb{N}}_{32} \oplus w_3\bar{\mathbb{N}}_{33} \rangle \\ &= \left\langle \begin{aligned} &(0.364(\{0.9, 1\}, \{0.2\}, \{0\}) \oplus 0.223(\{0.5, 0.7\}, \{0.2, 0.3\}, \{0, 0.1\}) \oplus 0.413(\{0.4\}, \{0.6\}, \{0, 0.2\})), \\ &(0.364(\{0.8, 1\}, \{0, 0.2\}, \{0\}) \oplus 0.223(\{.6\}, \{0, 0.4\}, \{0, 0.2\}) \oplus 0.413(\{0.6, 0.8\}, \{0, 0.2\}, \{0, 0.3\})) \end{aligned} \right\rangle \\ &= \langle \langle \{0.6823, 1\}, \{0.3250, 0.3541\}, \{0\} \rangle, \langle \{0.6862, 1\}, \{0, 0.2350\}, \{0\} \rangle \rangle. \end{aligned}$$

For alternative \mathbb{A}_4 :

Let $\mathbb{N}_{41} = \langle \langle \{0.6, 0.7\}, \{0.3\}, \{0.1\} \rangle, \langle \{0.8, 1\}, \{0.2\}, \{0\} \rangle \rangle$

Let $\mathbb{N}_{42} = \langle \langle \{0.3\}, \{0.7\}, \{0.8, 1\} \rangle, \langle \{0.6, 0.7\}, \{0.2, 0.3\}, \{0.1\} \rangle \rangle$

Let $\mathbb{N}_{43} = \langle \langle \{0, 0.2\}, \{0.8\}, \{0.9\} \rangle, \langle \{0.5, 0.8\}, \{0.2\}, \{0.3\} \rangle \rangle$

The aggregated MVRNN for $\mathbb{A}^w_{MVRN}[\mathbb{A}_4|\mathbb{C}_1, \mathbb{C}_2, \mathbb{C}_3]$ is calculated as:

$$\begin{aligned} \mathbb{A}^w_{MVRN}[\mathbb{A}_4|\mathbb{C}_1, \mathbb{C}_2, \mathbb{C}_3] &= \langle w_1\mathbb{N}_{41} \oplus w_2\mathbb{N}_{42} \oplus w_3\mathbb{N}_{43}, w_1\bar{\mathbb{N}}_{41} \oplus w_2\bar{\mathbb{N}}_{42} \oplus w_3\bar{\mathbb{N}}_{43} \rangle \\ &= \left\langle \begin{aligned} &(0.364(\{0.6, 0.7\}, \{0.3\}, \{0.1\}) \oplus 0.223(\{0.3\}, \{0.7\}, \{0.8, 1\}) \oplus 0.413(\{0, 0.2\}, \{0.8\}, \{0.9\})), \\ &(0.364(\{0.8, 1\}, \{0.2\}, \{0\}) \oplus 0.223(\{0.6, 0.7\}, \{0.2, 0.3\}, \{0.1\}) \oplus 0.413(\{0.5, 0.8\}, \{0.2\}, \{0.3\})) \end{aligned} \right\rangle \\ &= \langle \langle \{0.3107, 0.4369\}, \{0.5631\}, \{0.4471, 0.4866\} \rangle, \langle \{0.6535, 1\}, \{0.2, 0.2194\}, \{0\} \rangle \rangle. \end{aligned}$$

Step 4: Compute score and accuracy metrics. Using Eqs. (11) and (12), we calculate each alternative's score (s) and accuracy (a) functions for the aggregated MVRNNs:

$$s(\mathbb{A}_1) = 0.8402, \quad s(\mathbb{A}_2) = 0.5958, \quad s(\mathbb{A}_3) = 0.9426, \quad s(\mathbb{A}_4) = 0.5470.$$

Step 5: Rank alternatives.

The alternatives are ranked based on their scores in descending order as follows:

$$\mathbb{A}_3 > \mathbb{A}_1 > \mathbb{A}_4 > \mathbb{A}_2.$$

Therefore, \mathbb{A}_3 (Multi-Speciality Hospital) is identified as the best choice.

Method 3: Multi-valued rough neutrosophic geometric mean operator

This method employs the MVRNGMO for aggregation, offering an alternative perspective to the arithmetic mean.

Step 1: Construct the decision matrix.

The decision matrix is constructed using MVRNNs, as described in previous methods Table 2.

Step 2: Aggregate the decision matrix.

We apply the aggregation operator to each alternative.

For alternative \mathbb{A}_1 :

Let $\mathbb{N}_{11} = \langle \langle \{0.7\}, \{0.3\}, \{0, 0.2\} \rangle, \langle \{0.9, 1\}, \{0.1, 0.2\}, \{0\} \rangle \rangle$

Let $\mathbb{N}_{12} = \langle \langle \{0.4\}, \{0.6\}, \{0.5\} \rangle, \langle \{0.7\}, \{0.3\}, \{0, 0.2\} \rangle \rangle$

Let $\mathbb{N}_{13} = \langle \langle \{0.5, 0.8\}, \{0.2, 0.3\}, \{0.1\} \rangle, \langle \{0.6, 0.9\}, \{0.2, 0.4\}, \{0.2\} \rangle \rangle$

The aggregated MVRNN for $\mathbb{G}_{MVRN}[\mathbb{A}_1|\mathbb{C}_1, \mathbb{C}_2, \mathbb{C}_3]$ is calculated as:

$$\mathbb{G}_{MVRN}[\mathbb{A}_1|\mathbb{C}_1, \mathbb{C}_2, \mathbb{C}_3] = \left\langle (\mathbb{N}_{11} \otimes \mathbb{N}_{12} \otimes \mathbb{N}_{13})^{\frac{1}{3}}, (\bar{\mathbb{N}}_{11} \otimes \bar{\mathbb{N}}_{12} \otimes \bar{\mathbb{N}}_{13})^{\frac{1}{3}} \right\rangle$$

$$= \left\langle \left((\{0.7\}, \{0.3\}, \{0, 0.2\}) \otimes (\{0.4\}, \{0.6\}, \{0.5\}) \otimes (\{0.5, 0.8\}, \{0.2, 0.3\}, \{0.1\}) \right)^{\frac{1}{3}}, \right. \\ \left. \left((\{0.9, 1\}, \{0.1, 0.2\}, \{0\}) \otimes (\{0.7\}, \{0.3\}, \{0, 0.2\}) \otimes (\{0.6, 0.9\}, \{0.2, 0.4\}, \{0.2\}) \right)^{\frac{1}{3}} \right\rangle \\ = \left\langle (\{0.5244, 0.6185\}, \{0.3815, 0.4115\}, \{0.2132, 0.2767\}), \right. \\ \left. (\{0.7291, 0.8642\}, \{0.2014, 0.3022\}, \{0.0675, 0.1343\}) \right\rangle.$$

For alternative A_2 :

Let $N_{21} = \langle \langle \{0.4\}, \{0.6\}, \{0.3\} \rangle, \langle \{0.8, 1\}, \{0.1, 0.2\}, \{0\} \rangle \rangle$

Let $N_{22} = \langle \langle \{0.7\}, \{0.3\}, \{0.2\} \rangle, \langle \{0.8, 0.9\}, \{0.1\}, \{0\} \rangle \rangle$

Let $N_{23} = \langle \langle \{0.3\}, \{0.7\}, \{0.8, 1\} \rangle, \langle \{0.7\}, \{0.3\}, \{0.1\} \rangle \rangle$

The aggregated MVRNN for $G_{MVRN}[A_2|C_1, C_2, C_3]$ is calculated as:

$$G_{MVRN}[A_2|C_1, C_2, C_3] = \left\langle (\underline{N}_{21} \otimes \underline{N}_{22} \otimes \underline{N}_{23})^{\frac{1}{3}}, (\overline{N}_{21} \otimes \overline{N}_{22} \otimes \overline{N}_{23})^{\frac{1}{3}} \right\rangle \\ = \left\langle \left((\{0.4\}, \{0.6\}, \{0.3\}) \otimes (\{0.7\}, \{0.3\}, \{0.2\}) \otimes (\{0.3\}, \{0.7\}, \{0.8, 1\}) \right)^{\frac{1}{3}}, \right. \\ \left. \left((\{0.8, 1\}, \{0.1, 0.2\}, \{0\}) \otimes (\{0.8, 0.9\}, \{0.1\}, \{0\}) \otimes (\{0.7\}, \{0.3\}, \{0.1\}) \right)^{\frac{1}{3}} \right\rangle \\ = \langle \langle \{0.4465\}, \{0.5534\}, \{0.4907, 1\} \rangle, \langle \{0.7661, 0.8642\}, \{0.1669, 0.2014\}, \{0.0334\} \rangle \rangle.$$

For alternative A_3 :

Let $N_{31} = \langle \langle \{0.9, 1\}, \{0.2\}, \{0\} \rangle, \langle \{0.8, 1\}, \{0, 0.2\}, \{0\} \rangle \rangle$

Let $N_{32} = \langle \langle \{0.5, 0.7\}, \{0.2, 0.3\}, \{0, 0.1\} \rangle, \langle \{.6\}, \{0, 0.4\}, \{0, 0.2\} \rangle \rangle$

Let $N_{33} = \langle \langle \{0.4\}, \{0.6\}, \{0, 0.2\} \rangle, \langle \{0.6, 0.8\}, \{0, 0.2\}, \{0, 0.3\} \rangle \rangle$

The aggregated MVRNN for $G_{MVRN}[A_3|C_1, C_2, C_3]$ is calculated as:

$$G_{MVRN}[A_3|C_1, C_2, C_3] = \left\langle (\underline{N}_{31} \otimes \underline{N}_{32} \otimes \underline{N}_{33})^{\frac{1}{3}}, (\overline{N}_{31} \otimes \overline{N}_{32} \otimes \overline{N}_{33})^{\frac{1}{3}} \right\rangle \\ = \left\langle \left((\{0.9, 1\}, \{0.2\}, \{0\}) \otimes (\{0.5, 0.7\}, \{0.2, 0.3\}, \{0, 0.1\}) \otimes (\{0.4\}, \{0.6\}, \{0, 0.2\}) \right)^{\frac{1}{3}}, \right. \\ \left. \left((\{0.8, 1\}, \{0, 0.2\}, \{0\}) \otimes (\{.6\}, \{0, 0.4\}, \{0, 0.2\}) \otimes (\{0.6, 0.8\}, \{0, 0.2\}, \{0, 0.3\}) \right)^{\frac{1}{3}} \right\rangle \\ = \langle \langle \{0.5801, 0.6777\}, \{0.3506, 0.3815\}, \{0, 0.1007\} \rangle, \langle \{0.6636, 0.7941\}, \{0, 0.2648\}, \{0, 0.1691\} \rangle \rangle.$$

For alternative A_4 :

Let $N_{41} = \langle \langle \{0.6, 0.7\}, \{0.3\}, \{0.1\} \rangle, \langle \{0.8, 1\}, \{0.2\}, \{0\} \rangle \rangle$

Let $N_{42} = \langle \langle \{0.3\}, \{0.7\}, \{0.8, 1\} \rangle, \langle \{0.6, 0.7\}, \{0.2, 0.3\}, \{0.1\} \rangle \rangle$

Let $N_{43} = \langle \langle \{0, 0.2\}, \{0.8\}, \{0.9\} \rangle, \langle \{0.5, 0.8\}, \{0.2\}, \{0.3\} \rangle \rangle$

The aggregated MVRNN for $G_{MVRN}[A_4|C_1, C_2, C_3]$ is calculated as:

$$G_{MVRN}[A_4|C_1, C_2, C_3] = \left\langle (\underline{N}_{41} \otimes \underline{N}_{42} \otimes \underline{N}_{43})^{\frac{1}{3}}, (\overline{N}_{41} \otimes \overline{N}_{42} \otimes \overline{N}_{43})^{\frac{1}{3}} \right\rangle \\ = \left\langle \left((\{0.6, 0.7\}, \{0.3\}, \{0.1\}) \otimes (\{0.3\}, \{0.7\}, \{0.8, 1\}) \otimes (\{0, 0.2\}, \{0.8\}, \{0.9\}) \right)^{\frac{1}{3}}, \right. \\ \left. \left((\{0.8, 1\}, \{0.2\}, \{0\}) \otimes (\{0.6, 0.7\}, \{0.2, 0.3\}, \{0.1\}) \otimes (\{0.5, 0.8\}, \{0.2\}, \{0.3\}) \right)^{\frac{1}{3}} \right\rangle \\ = \langle \langle \{0, 0.3598\}, \{0.6402\}, \{0.7116, 1\} \rangle, \langle \{0.6270, 0.8309\}, \{0.2, 0.2339\}, \{1\} \rangle \rangle.$$

Step 3: Compute score and accuracy metrics. Using Eqs. (11) and (12), we calculate each alternative’s score (s) and accuracy (a) functions for the aggregated MVRNNs:

$$s(A_1) = 0.6814, \quad s(A_2) = 0.5020, \quad s(A_3) = 0.8065, \quad s(A_4) = 0.0847.$$

Step 4: Rank alternatives. The alternatives are ranked based on their scores in descending order as follows:

$$A_3 > A_1 > A_2 > A_4.$$

Therefore, A_3 (Multi-Speciality Hospital) is identified as the best choice.

Method 4: Weighted multi-valued rough neutrosophic geometric mean operator

This method combines the geometric mean aggregation with criteria weights, using the WMVRNGMO.

Step 1: Construct the decision matrix.

The MVRNN-based decision matrix is constructed as in previous methods [Table 2](#).

Step 2: Determine criteria weights.

The criteria weights (w_1, w_2, w_3) are determined using the Shapley fuzzy measure, as detailed in the “Fuzzy Measure of Attributes and Criteria Weights” subsection. The calculated weights are: $w_1 = 0.364, w_2 = 0.223, w_3 = 0.413$

Step 3: Calculate weighted aggregation values.

By utilizing [Eq. \(10\)](#), the aggregation values are computed for each alternative. For clarity, the aggregation for each alternative is shown with its constituent MVRNNs and their respective weights.

For alternative A_1 :

Let $N_{11} = \langle \langle \{0.7\}, \{0.3\}, \{0, 0.2\} \rangle, \langle \{0.9, 1\}, \{0.1, 0.2\}, \{0\} \rangle \rangle$

Let $N_{12} = \langle \langle \{0.4\}, \{0.6\}, \{0.5\} \rangle, \langle \{0.7\}, \{0.3\}, \{0, 0.2\} \rangle \rangle$

Let $N_{13} = \langle \langle \{0.5, 0.8\}, \{0.2, 0.3\}, \{0.1\} \rangle, \langle \{0.6, 0.9\}, \{0.2, 0.4\}, \{0.2\} \rangle \rangle$

The aggregated MVRNN for $G^w_{MVRN}[A_1|C_1, C_2, C_3]$ is calculated as:

$$\begin{aligned} G^w_{MVRN}[A_1|C_1, C_2, C_3] &= \langle (N_{11})^{w_1} \otimes (N_{12})^{w_2} \otimes (N_{13})^{w_3}, (\bar{N}_{11})^{w_1} \otimes (\bar{N}_{12})^{w_2} \otimes (\bar{N}_{13})^{w_3} \rangle \\ &= \left\langle \left((\{0.7\}, \{0.3\}, \{0, 0.2\})^{0.364} \otimes (\{0.4\}, \{0.6\}, \{0.5\})^{0.223} \otimes (\{0.5, 0.8\}, \{0.2, 0.3\}, \{0.1\})^{0.413} \right), \right. \\ &\quad \left. \left((\{0.9, 1\}, \{0.1, 0.2\}, \{0\})^{0.364} \otimes (\{0.7\}, \{0.3\}, \{0, 0.2\})^{0.223} \otimes (\{0.6, 0.9\}, \{0.2, 0.4\}, \{0.2\})^{0.413} \right) \right\rangle \\ &= \left\langle \left(\{0.5425, 0.6628\}, \{0.3372, 0.3757\}, \{0.1625, 0.2334\} \right), \right. \\ &\quad \left. \left(\{0.7267, 0.89\}, \{0.1871, 0.3075\}, \{0.0835, 0.1282\} \right) \right\rangle. \end{aligned}$$

For alternative A_2 :

Let $N_{21} = \langle \langle \{0.4\}, \{0.6\}, \{0.3\} \rangle, \langle \{0.8, 1\}, \{0.1, 0.2\}, \{0\} \rangle \rangle$

Let $N_{22} = \langle \langle \{0.7\}, \{0.3\}, \{0.2\} \rangle, \langle \{0.8, 0.9\}, \{0.1\}, \{0\} \rangle \rangle$

Let $N_{23} = \langle \langle \{0.3\}, \{0.7\}, \{0.8, 1\} \rangle, \langle \{0.7\}, \{0.3\}, \{0.1\} \rangle \rangle$

The aggregated MVRNN for $G^w_{MVRN}[A_2|C_1, C_2, C_3]$ is calculated as:

$$\begin{aligned} G^w_{MVRN}[A_2|C_1, C_2, C_3] &= \langle (N_{21})^{w_1} \otimes (N_{22})^{w_2} \otimes (N_{23})^{w_3}, (\bar{N}_{21})^{w_1} \otimes (\bar{N}_{22})^{w_2} \otimes (\bar{N}_{23})^{w_3} \rangle \\ &= \left\langle \left((\{0.4\}, \{0.6\}, \{0.3\})^{0.364} \otimes (\{0.7\}, \{0.3\}, \{0.2\})^{0.223} \otimes (\{0.3\}, \{0.7\}, \{0.8, 1\})^{0.413} \right), \right. \\ &\quad \left. \left((\{0.8, 1\}, \{0.1, 0.2\}, \{0\})^{0.364} \otimes (\{0.8, 0.9\}, \{0.1\}, \{0\})^{0.223} \otimes (\{0.7\}, \{0.3\}, \{0.1\})^{0.413} \right) \right\rangle \\ &= \langle \langle \{0.4088\}, \{0.5912\}, \{0.5452, 1\} \rangle, \langle \{0.7581, 0.8509\}, \{0.1846, 0.2203\}, \{0.0414\} \rangle \rangle. \end{aligned}$$

For alternative A_3 :

Let $N_{31} = \langle \langle \{0.9, 1\}, \{0.2\}, \{0\} \rangle, \langle \{0.8, 1\}, \{0, 0.2\}, \{0\} \rangle \rangle$

Let $N_{32} = \langle \langle \{0.5, 0.7\}, \{0.2, 0.3\}, \{0, 0.1\} \rangle, \langle \{.6\}, \{0, 0.4\}, \{0, 0.2\} \rangle \rangle$

Let $N_{33} = \langle \langle \{0.4\}, \{0.6\}, \{0, 0.2\} \rangle, \langle \{0.6, 0.8\}, \{0, 0.2\}, \{0, 0.3\} \rangle \rangle$

The aggregated MVRNN for $G^w_{MVRN}[A_3|C_1, C_2, C_3]$ is calculated as:

$$\begin{aligned} G^w_{MVRN}[A_3|C_1, C_2, C_3] &= \langle (N_{31})^{w_1} \otimes (N_{32})^{w_2} \otimes (N_{33})^{w_3}, (\bar{N}_{31})^{w_1} \otimes (\bar{N}_{32})^{w_2} \otimes (\bar{N}_{33})^{w_3} \rangle \\ &= \left\langle \left((\{0.9, 1\}, \{0.2\}, \{0\})^{0.364} \otimes (\{0.5, 0.7\}, \{0.2, 0.3\}, \{0, 0.1\})^{0.223} \otimes (\{0.4\}, \{0.6\}, \{0, 0.2\})^{0.413} \right), \right. \\ &\quad \left. \left((\{0.8, 1\}, \{0, 0.2\}, \{0\})^{0.364} \otimes (\{.6\}, \{0, 0.4\}, \{0, 0.2\})^{0.223} \otimes (\{0.6, 0.8\}, \{0, 0.2\}, \{0, 0.3\})^{0.413} \right) \right\rangle \\ &= \langle \langle \{0.5819, 0.6589\}, \{0.3845, 0.4046\}, \{0, 0.1057\} \rangle, \langle \{0.6697, 0.8236\}, \{0, 0.2468\}, \{0, 0.1714\} \rangle \rangle. \end{aligned}$$

For alternative \mathbb{A}_4 :

Let $\mathbb{N}_{41} = \langle \langle \{0.6, 0.7\}, \{0.3\}, \{0.1\} \rangle, \langle \{0.8, 1\}, \{0.2\}, \{0\} \rangle \rangle$

Let $\mathbb{N}_{42} = \langle \langle \{0.3\}, \{0.7\}, \{0.8, 1\} \rangle, \langle \{0.6, 0.7\}, \{0.2, 0.3\}, \{0.1\} \rangle \rangle$

Let $\mathbb{N}_{43} = \langle \langle \{0, 0.2\}, \{0.8\}, \{0.9\} \rangle, \langle \{0.5, 0.8\}, \{0.2\}, \{0.3\} \rangle \rangle$

The aggregated MVRNN for $\mathbb{G}^w_{MVRN}[\mathbb{A}_4 | \mathbb{C}_1, \mathbb{C}_2, \mathbb{C}_3]$ is calculated as:

$$\begin{aligned} \mathbb{G}^w_{MVRN}[\mathbb{A}_4 | \mathbb{C}_1, \mathbb{C}_2, \mathbb{C}_3] &= \langle (\mathbb{N}_{41})^{w_1} \otimes (\mathbb{N}_{42})^{w_2} \otimes (\mathbb{N}_{43})^{w_3}, (\bar{\mathbb{N}}_{41})^{w_1} \otimes (\bar{\mathbb{N}}_{42})^{w_2} \otimes (\bar{\mathbb{N}}_{43})^{w_3} \rangle \\ &= \left\langle \left((\{0.6, 0.7\}, \{0.3\}, \{0.1\})^{0.364} \otimes (\{0.3\}, \{0.7\}, \{0.8, 1\})^{0.223} \otimes (\{0, 0.2\}, \{0.8\}, \{0.9\})^{0.413} \right), \right. \\ &\quad \left. \left((\{0.8, 1\}, \{0.2\}, \{0\})^{0.364} \otimes (\{0.6, 0.7\}, \{0.2, 0.3\}, \{0.1\})^{0.223} \otimes (\{0.5, 0.8\}, \{0.2\}, \{0.3\})^{0.413} \right) \right\rangle \\ &= \langle (\{0.00, 0.3595\}, \{0.6410\}, \{0.7112, 1\}), (\{0.6246, 0.8484\}, \{0.2, 0.2228\}, \{0.1491\}) \rangle. \end{aligned}$$

Step 4: Compute score and accuracy metrics. Using Eqs. (11) and (12), we calculate each alternative’s score (s) and accuracy (a) functions for the aggregated MVRNNs:

$$s(\mathbb{A}_1) = 0.7249, \quad s(\mathbb{A}_2) = 0.4530, \quad s(\mathbb{A}_3) = 0.7982, \quad s(\mathbb{A}_4) = 0.3017.$$

Step 5: Rank alternatives. The alternatives are ranked based on their scores in descending order as follows:

$$\mathbb{A}_3 > \mathbb{A}_1 > \mathbb{A}_2 > \mathbb{A}_4.$$

Therefore, \mathbb{A}_3 (Multi-Speciality Hospital) is identified as the best choice.

Results and discussion

The ranking results of four hospitals (\mathbb{A}_1 to \mathbb{A}_4), using MVRNNs-based methods are presented. Table 3 shows the scores and ranks for each method.

The Multi-Speciality Hospital consistently attains the highest ranking across all methods, followed by private, government, and charity hospitals. The consistent results show the method’s effectiveness and stability under uncertainty. The rankings are presented in Fig. 2, a bar chart created using MATLAB.

Table 3. The ranking results of four MCDM approaches.

Alternative	Method 1	Rank	Method 2	Rank	Method 3	Rank	Method 4	Rank
\mathbb{A}_1	0.7940	II	0.8402	II	0.6814	II	0.7249	II
\mathbb{A}_2	0.6581	III	0.5958	III	0.5020	III	0.4530	III
\mathbb{A}_3	0.9468	I	0.9426	I	0.8065	I	0.7982	I
\mathbb{A}_4	0.4274	IV	0.5470	IV	0.0847	IV	0.3017	IV

Discussion on ranking consistency

All four aggregation operators (MVRNAMO, WMVRNAMO, MVRNGMO, WMVRNGMO) produce the same ranking:

$$\mathbb{A}_3 > \mathbb{A}_1 > \mathbb{A}_2 > \mathbb{A}_4.$$

This consistency is due to the strong performance of the Multi-Speciality Hospital (\mathbb{A}_3) across all criteria, making the results robust to different aggregation methods. Although weighted operators use Shapley-based weights, they don’t change the final ranking in this case. This shows that when performance differences are large, results remain stable, while in closer cases, the choice of operator and weights may influence the ranking.

Software used for calculations

All numerical computations, from MVRNN aggregation to score and accuracy calculations, and the final ranking, were performed using MATLAB. This software offered a robust platform for executing intricate mathematical operations and confirming the outcomes.

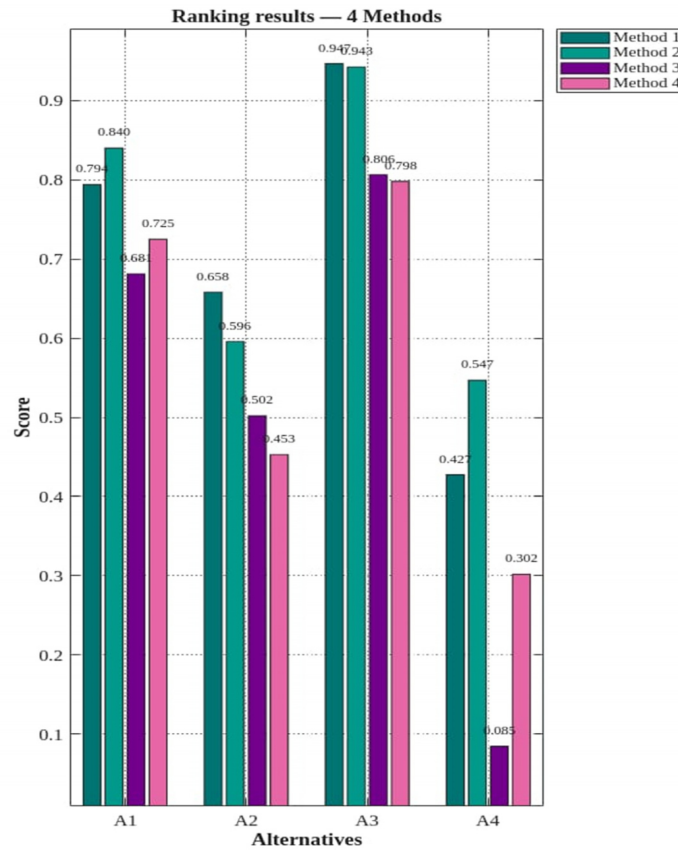


Fig. 2. MATLAB-generated bar chart showing the rankings of the hospital alternatives.

Comparative analysis

To rigorously validate the effectiveness and robustness of our proposed MVRNN-based aggregation operators, we conduct a comprehensive comparative analysis with several prominent MCDM methods from the existing literature. Specifically, we compare our framework against:

1. An Aczel-Alsina aggregation-based outranking method for single-valued neutrosophic numbers (SVNNs) by Senapati et al.,⁵⁷ including SVNAAWA, SVNAAOWA, and SVNAAHA operators.
2. Single-Valued Neutrosophic Dombi Weighted Averaging Aggregation Operators (SVNDWAA and SVNDWGA) by Chen and Ye.¹⁴
3. Dual Generalized Single-Valued Neutrosophic Bonferroni Mean (DGSNNWBM) and Dual Hesitant Single-Valued Neutrosophic Weighted Geometric Bonferroni Mean (DHSVNNWGBM) Operators by Wang et al.⁵⁸
4. Neutrosophic Hesitant Fuzzy Heronian Mean Aggregation Operators (NHFIGWHM and NHFIGGWHM) by Liu and Zhang.⁵⁹

Data transformation and method application

To facilitate direct comparison, our initial MVRNN decision matrix [Table 2](#) is transformed into formats compatible with each comparative method. The transformation process is as follows:

1. MVRNN to MVNN Conversion: First, the MVRNNs are converted into MVNNs using the accumulated geometric operator as proposed by Martina DJ, Deepa G.² This involves combining the lower and upper approximations of each MVRNN element into a single set of multi-values.

2. MVNN to SVNN Conversion: For Senapati's,⁵⁷ Chen and Ye's,¹⁴ and Wang et al.'s⁵⁸ methods (all of which operate on SVNNs), these MVNNs are further converted into SVNNs by taking the mean of their multi-values within each truth, indeterminacy, and falsity component.
3. MVNN to Neutrosophic Hesitant Fuzzy Set (NHFS) Conversion: For Liu and Zhang's⁵⁹ methods, these MVNNs are converted into NHFSs.

The criteria weights ($w_1 = 0.364$, $w_2 = 0.223$, $w_3 = 0.413$) derived from the Shapley fuzzy measure are consistently applied where applicable.

Comparative ranking results

The final scores and ranking of alternatives obtained from applying the comparative methods, alongside our proposed MVRNN-based framework, are summarized in Table 4.

Table 4. Comparative ranking results of proposed and existing methods.

Method	\mathbb{A}_1	\mathbb{A}_2	\mathbb{A}_3	\mathbb{A}_4	Ranking
SVNAAWA Operator ⁵⁷	0.8159	0.7615	0.8746	0.7298	$\mathbb{A}_3 > \mathbb{A}_1 > \mathbb{A}_2 > \mathbb{A}_4$
SVNAAOWA Operator ⁵⁷	0.7588	0.7120	0.8725	0.6609	$\mathbb{A}_3 > \mathbb{A}_1 > \mathbb{A}_2 > \mathbb{A}_4$
SVNDWAA Operator ¹⁴	0.8243	0.7765	0.9008	0.7556	$\mathbb{A}_3 > \mathbb{A}_1 > \mathbb{A}_2 > \mathbb{A}_4$
SVNDWGA Operator ¹⁴	0.7642	0.6971	0.8093	0.5401	$\mathbb{A}_3 > \mathbb{A}_1 > \mathbb{A}_2 > \mathbb{A}_4$
DGSVNNWBM Operator ⁵⁸	0.7653	0.7039	0.8112	0.6015	$\mathbb{A}_3 > \mathbb{A}_1 > \mathbb{A}_2 > \mathbb{A}_4$
DGSVNNWGBM Operator ⁵⁸	0.8020	0.7492	0.8364	0.6773	$\mathbb{A}_3 > \mathbb{A}_1 > \mathbb{A}_2 > \mathbb{A}_4$
NHFIGWHM Operator ⁵⁹	0.8175	0.7522	0.8682	0.7257	$\mathbb{A}_3 > \mathbb{A}_1 > \mathbb{A}_2 > \mathbb{A}_4$
NHFIGWHM Operator ⁵⁹	0.6988	0.6707	0.7565	0.6353	$\mathbb{A}_3 > \mathbb{A}_1 > \mathbb{A}_2 > \mathbb{A}_4$
(WMVRNAMO) Proposed Operator	0.8402	0.5958	0.9426	0.5470	$\mathbb{A}_3 > \mathbb{A}_1 > \mathbb{A}_2 > \mathbb{A}_4$
(WMVRNGMO) Proposed Operator	0.7249	0.4530	0.7982	0.3017	$\mathbb{A}_3 > \mathbb{A}_1 > \mathbb{A}_2 > \mathbb{A}_4$

Discussion

The comparative analysis reveals a remarkable consistency in the final ranking of alternatives across all investigated methods, both our proposed MVRNN-based framework and the four prominent existing approaches (Senapati's SVNAAWA,⁵⁷ Chen and Ye's SVNDWAA,¹⁴ Wang et al.'s DGSNNWBM,⁵⁸ and Liu and Zhang's NHFIGWHM.⁵⁹) In every instance, Alternative \mathbb{A}_3 (Multi-Speciality Hospital) consistently emerged as the top-ranked choice, followed by \mathbb{A}_1 , \mathbb{A}_2 , and \mathbb{A}_4 .

In spite of this consistency, the MVRN-based framework presents distinct benefits when modeling the intricacies of real-world scenarios. Unlike SVNN-based methodologies, which tend to simplify expert assessments, the proposed framework inherently accommodates multi-valued information, rough approximations, and the complete range of truth, indeterminacy, and falsity. The MVRNN structure, by directly incorporating multiple, potentially conflicting expert evaluations, facilitates a more detailed and realistic evaluation. Although the ultimate ranking remained unchanged in this instance, the framework offers a comprehensive and theoretically sound approach, adept at managing vagueness and uncertainty while yielding more profound insights into the decision-making process.

Conclusion

This paper proposes a new MCDM framework based on MVRNNs to handle decision-making problems with uncertainty, vagueness, and inconsistency. Four new aggregation operators (MVRNAMO, WMVRNAMO, MVRNGMO, WMVRNGMO) are introduced with proven properties such as idempotency, boundedness, and monotonicity. The Shapley fuzzy measure is used for effective criteria weighting, and new score and accuracy functions are defined for ranking alternatives. A hospital selection case study demonstrates the effectiveness of the model, where the Multi-Speciality Hospital consistently ranks as the best alternative, confirming the stability and reliability of the proposed approach.

Advantages, limitations, and future work

The proposed framework effectively handles different types of uncertainty, such as vagueness, indeterminacy, and rough information, while providing flexible and consistent rankings through various aggregation operators.

The use of Shapley fuzzy measures enhances the accurate evaluation of the importance of criteria. However, the framework may face challenges with large datasets and situations involving highly conflicting expert opinions. Future work can focus on improving computational efficiency, applying the method to diverse real-world problems such as energy, engineering, and environmental management, and developing automated and real-time decision-making tools.

Authors' declaration

- Conflicts of Interest: None.
- We hereby confirm that all the Figures and Tables in the manuscript are ours. Furthermore, any Figures and images that are not ours have been included with the necessary permission for republication, which is attached to the manuscript.
- No animal studies are present in the manuscript.
- No human studies are present in the manuscript.
- Ethical Clearance: The project was approved by the local ethical committee at Vellore Institute of Technology, Vellore, India.

Authors' contribution statement

K.G. and G.D. were responsible for the design and implementation of the research. K.G. performed drafting the manuscript, conducted the analysis, acquired data, interpreted the results, and contributed to the writing of the manuscript. G.D. did the revision and interpretation. All authors read and agreed upon the published version of the manuscript.

Funding statement

This research work was supported and funded by Vellore Institute of Technology, Vellore, Tamil Nadu, India.

References

1. Martina DJ, Deepa G. Some algebraic properties on rough neutrosophic matrix and its application to multi-criteria decision-making. *AIMS Math.* 2023;8(10):24132–52. <https://doi.org/10.3934/math.20231230>.
2. Martina DJ, Deepa G. Application of multi-valued rough neutrosophic set and matrix in multi-criteria decision-making: Multi-valued neutrosophic rough set and matrix. *Math Appl Sci Eng.* 2023 Sep;4(3):227–48. <https://doi.org/10.5206/mase/16636>.
3. Zadeh LA. Fuzzy sets. *Inf Control.* 1965 Jun;8(3):338–53. [https://doi.org/10.1016/S0019-9958\(65\)90241-X](https://doi.org/10.1016/S0019-9958(65)90241-X).
4. Atanassov KT. Intuitionistic fuzzy sets. *Fuzzy Sets Syst.* 1986;20(1):87–96. [https://doi.org/10.1016/S0165-0114\(86\)80034-3](https://doi.org/10.1016/S0165-0114(86)80034-3).
5. Smarandache F. A geometric interpretation of the neutrosophic set, a generalization of the intuitionistic fuzzy set. *Int J Pure Appl Math.* 2005;24(3):287–97. <https://doi.org/10.48550/arXiv.math/0404520>.
6. Peng JJ, Wang JQ. Multi-valued neutrosophic sets and its application in multi-criteria decision-making problems. *Neutrosophic Sets Syst.* 2015 Jan;10:3–17.
7. Pawlak Z. Rough sets. *Int J Comput Inf Sci.* 1982 Oct;11:341–56. <https://doi.org/10.1007/BF01001956>.
8. Dubois D, Prade H. Rough fuzzy sets and fuzzy rough sets. *Int J Gen Syst.* 1990 Jun;17(2/3):191–209. <https://doi.org/10.1080/03081079008935107>.
9. Broumi S, Smarandache F, Dhar M. Rough neutrosophic sets. *Neutrosophic Sets Syst.* 2014;3:60–5.
10. Jin Q, Hu K, Bo C, Li L. A new single-valued neutrosophic rough sets and related topology. *J Math.* 2021;2021:5522021. <https://doi.org/10.1155/2021/5522021>.
11. Yao YY. Relational interpretations of neighborhood operators and rough set approximation operators. *Inf Sci.* 1998 Nov;111(1–4):239–259. [https://doi.org/10.1016/S0020-0255\(98\)10006-3](https://doi.org/10.1016/S0020-0255(98)10006-3).
12. Smarandache F. A unifying field in logics: Neutrosophic logic, neutrosophic set, neutrosophic probability and statistics. *arXiv preprint math/0101228.* 2010 Jan 28. <https://doi.org/10.48550/arXiv.math/0101228>.
13. Mondal K, Pramanik S, Giri BC. Rough neutrosophic aggregation operators for multi-criteria decision-making. In: *Fuzzy Multi-criteria Decision-Making Using Neutrosophic Sets Springer*; 2019;13:79–105. https://doi.org/10.1007/978-3-030-00045-5_5.
14. Chen J, Ye J. Some single-valued neutrosophic Dombi weighted aggregation operators for multiple attribute decision-making. *Symmetry.* 2017 Jun 2;9(6):82. <https://doi.org/10.3390/sym9060082>.
15. Cui WH, Ye J, Xue JJ, Hu KL. Weighted aggregation operators of single-valued neutrosophic linguistic neutrosophic sets and their decision-making method. *Neutrosophic Sets Syst.* 2022;5(2):22–32.
16. Mahmood A, Abbas M, Murtaza G. Multi-valued multi-polar neutrosophic sets with an application in multi-criteria decision-making. *Neutrosophic Sets Syst.* 2023;53(1):32.

17. Awang A, Aizam NA, Ab Ghani AT, Othman M, Abdullah L. A normalized weighted bonferroni mean aggregation operator considering shapley fuzzy measure under interval-valued neutrosophic environment for decision-making. *Int J Fuzzy Syst.* 2020 Feb;22:321–36. <https://doi.org/10.1007/s40815-019-00752-5>.
18. Zhang W, Ju Y, Liu X. Multiple criteria decision analysis based on Shapley fuzzy measures and interval-valued hesitant fuzzy linguistic numbers. *Comput Ind Eng.* 2017 Mar;105:28–38. <https://doi.org/10.1016/j.cie.2016.12.046>.
19. Wang L, Bao YL. Multiple-attribute decision-making method based on normalized geometric aggregation operators of single-valued neutrosophic hesitant fuzzy information. *Complexity.* 2021;2021:1–15. <https://doi.org/10.1155/2021/5580761>.
20. Karaaslan F, Ahmed MTA, Dawood MAD. Distance measures of hesitant complex neutrosophic sets and their applications in decision-making. *Comput Appl Math.* 2022;41(7):1–36. <https://doi.org/10.1007/s40314-022-02009-8>.
21. Ahmad F, John B. Modeling and optimization of multiobjective programming problems in neutrosophic hesitant fuzzy environment. *Soft Comput.* 2022;26(12):5719–5739. <https://doi.org/10.1007/s00500-022-06953-9>.
22. Seikh MR, Dutta S. A nonlinear programming model to solve matrix games with pay-offs of single-valued neutrosophic numbers. *Neutrosophic Sets Syst.* 2021;47:366–383.
23. Seikh MR, Dutta S. Solution of matrix games with pay-offs of single-valued trapezoidal neutrosophic numbers. *Soft Comput.* 2022;26(3):921–936. <https://doi.org/10.1007/s00500-021-06559-7>.
24. Seikh MR, Dutta S. Interval neutrosophic matrix game-based approach to counter cybersecurity issue. *Granul Comput.* 2023;8(2):271–292. <https://doi.org/10.1007/s41066-022-00327-0>.
25. Ye J, Song J, Du S. Correlation coefficients of consistency neutrosophic sets regarding neutrosophic multi-valued sets and their multi-attribute decision-making method. *Int J Fuzzy Syst.* 2022 Mar;24(2):925–932. <https://doi.org/10.1007/s40815-020-00983-x>.
26. Abobala M, Hatip A. An algebraic approach to neutrosophic Euclidean geometry. *Neutrosophic Sets Syst.* 2021 Jul 9;43:114–123.
27. Farid HM, Riaz M. Single-valued neutrosophic Einstein interactive aggregation operators with applications for material selection in engineering design: case study of cryogenic storage tank. *Complex Intell Syst.* 2022 Jun;8(3):2131–2149. <https://doi.org/10.1007/s40747-021-00626-0>.
28. Daher HY, Kider JR. Finite dimensional convex fuzzy normed space and its basic properties. *Baghdad Sci J.* 2025;22(4):1328–1334. <https://doi.org/10.21123/bsj.2024.10530>.
29. Peng JJ, Wang JQ, Wu XH, Wang J, Chen XH. Multi-valued neutrosophic sets and power aggregation operators with their applications in multi-criteria group decision-making problems. *Int J Comput Intell Syst.* 2015;8(2):345–363. <https://doi.org/10.1080/18756891.2015.1001957>.
30. Wang W, Huang B, Wang T. Optimal scale selection based on multi-scale single-valued neutrosophic decision-theoretic rough set with cost-sensitivity. *Int J Approx Reason.* 2023;155:132–144. <https://doi.org/10.1016/j.ijar.2023.02.003>.
31. Donbosco JS, Ganesan D. The Energy of rough neutrosophic matrix and its application to MCDM problem for selecting the best building construction site. *Decision Making: Applications in Management and Engineering.* 2022 Oct 5;5(2):30–45. <https://doi.org/10.31181/dmame0305102022d>.
32. Kamran M, Ashraf S, Salamat N, Naeem M, Hameed MS. Smart city design plan selection through single-valued neutrosophic probabilistic hesitant fuzzy rough aggregation information. *J Intell Fuzzy Syst.* 2023;45(6):10693–10737. <https://doi.org/10.3233/JIFS-224364>.
33. Kamran M, Ismail R, Al-Sabri EH, Salamat N, Farman M, Ashraf S. An optimization strategy for MADM framework with confidence level aggregation operators under probabilistic neutrosophic hesitant fuzzy rough environment. *Symmetry.* 2023;15(3):578(1–40). <https://doi.org/10.3390/sym15030578>.
34. Debnath S. Single-valued neutrosophic covering-based rough set model over two universes and its application in MCDM. *Neutrosophic Sets Syst.* 2023;53:482–507.
35. Kamran M, Ashraf S, Hameed MS. A promising approach with confidence level aggregation operators based on single-valued neutrosophic rough sets. *Soft Comput.* 2023 Oct 9:1–24. <https://doi.org/10.1007/s00500-023-09272-9>.
36. Kamran M, Salamat N, Ashraf S, Alam MA, Cangul IN. Novel decision modeling for manufacturing sustainability under single-valued neutrosophic hesitant fuzzy rough aggregation information. *Comput Intell Neurosci.* 2022;2022:7924094. <https://doi.org/10.1155/2022/7924094>.
37. Ye J, Türkarslan E, Ünver M, Olgun M. Algebraic and Einstein weighted operators of neutrosophic enthalpy values for multi-criteria decision making in neutrosophic multi-valued set settings. *Granul Comput.* 2022 Jul;7(3):479–487. <https://doi.org/10.1007/s41066-021-00279-x>.
38. Kamran M, Salamat N, Jana C, Xin Q. Decision-making technique with neutrosophic Z-rough set approach for sustainable industry evaluation using sine trigonometric operators. *Appl Soft Comput.* 2025 Jan 1;169:112539. <https://doi.org/10.1016/j.asoc.2024.112539>.
39. Elsayed A, Mohamed M. Comparative analysis of multi-criteria techniques in neutrosophic environment and their applications to economic condition assessment. *Neutrosophic Syst Appl.* 2024 Dec 1;24(1):63–83. <https://doi.org/10.61356/j.nswa.2024.24437>.
40. Xu D, Zhao Y. A new distance measure for single-valued neutrosophic set and an improved method based on TOPSIS and TODIM to multi-attribute decision-making. *Int J Knowl Based Intell Eng Syst.* 2025;29(3):322–335. <https://doi.org/10.1177/13272314241313146>.
41. Ali Z, Bibi H. Waste reduction and recycling: schweizer-sklar aggregation operators based on neutrosophic fuzzy rough sets and their application in green supply chain management. *Neutrosophic Syst Appl.* 2024 Jul 2;19(1):53–66. <https://doi.org/10.61356/j.nswa.2024.19324>.
42. Alias S, Mohamad D, Shuib A, Mustapha N, Yasin RM, Yusoff NS, Broumi S. Rough neutrosophic multisets geometric aggregation operator with entropy weight combined roughness dice similarity measure and its application. *ITM Web Conf.* 2024;67:01026. <https://doi.org/10.1051/itmconf/20246701026>.
43. Halim NQ, Awang NA, Yaacob SN, Hashim H, Sulaiman R, Abdullah L. Rough neutrosophic shapley weighted Einstein averaging aggregation operator and its application in multi-criteria decision-making problem. *Adv Sci Technol Eng Syst J.* 2023 Apr;43(2):52–64. <https://doi.org/10.37934/araset.43.2.5264>.

44. Yumashev A, Udayakumar P, Ramesh SN, Lydia EL, Kumar KV. Role of rough neutrosophic attribute reduction with deep learning-based enhanced kidney disease diagnosis. *Int J Neutrosophic Sci.* 2025;25(1):291–302. <https://doi.org/10.54216/IJNS.250126>.
45. Pratheesha SVA, Arora P, Wason R, Baliga BD. TOPSIS approach for MADM based on quadripartitioned single valued neutrosophic refined Hamacher aggregation operations. *Neutrosophic Sets Syst.* 2025;80(1):10.
46. Qiu H, Liu Z, Huang H, Letchmunan S, Deveci M, Senapati T. L2-regularization based two-way weighted neutrosophic clustering with Manhattan and Euclidean distances. *Fuzzy Sets Syst.* 2025;518:109507. <https://doi.org/10.1016/j.fss.2025.109507>.
47. Simic V, Dabic-Miletic S, Tirkolaee EB, Stevic Z, Deveci M, Senapati T. Neutrosophic CEBOM-MACONT model for sustainable management of end-of-life tires. *Appl Soft Comput.* 2023;143:110399. <https://doi.org/10.1016/j.asoc.2023.110399>.
48. Gokasar I, Simic V, Deveci M, Senapati T. Alternative prioritization of freeway incident management using autonomous vehicles in mixed traffic with a type-2 neutrosophic number-based decision support system. *Eng Appl Artif Intell.* 2023;123:106183. <https://doi.org/10.1016/j.engappai.2023.106183>.
49. Imran R, Ullah K, Ali Z, Akram M, Senapati T. The theory of prioritized muirhead mean operators under the presence of complex single-valued neutrosophic values. *Decis Anal J.* 2023;7:100214. <https://doi.org/10.1016/j.dajour.2023.100214>.
50. Mahmood T, Ali Z, Gumaie A. Interdependency of complex fuzzy neighborhood operators and derived complex fuzzy coverings. *IEEE Access.* 2021;9:73506–21. <https://doi.org/10.1109/ACCESS.2021.3074590>.
51. Zhou L, Abdullah S, Zafar H, Muhammad S, Qadir A, Huang H. Analysis of artificial neural network based on pq-rung orthopair fuzzy linguistic Muirhead mean operators. *Expert Syst Appl.* 2025;276:127157. <https://doi.org/10.1016/j.eswa.2025.127157>.
52. Khan J, Zafar H, Nawaz M. Double hierarchy linguistic soft and soft covering based sets and their application. *VFAST Trans Math.* 2025;13(1):41–58. <https://doi.org/10.21015/vtm.v13i1.2155>.
53. Ali Z, Yang MS. Analysis of renewable energies based on circular bipolar complex intuitionistic fuzzy linguistic information with Frank power aggregation operators and MABAC model. *Int J Comput Intell Syst.* 2025;18(1):1–40. <https://doi.org/10.1007/s44196-025-00800-z>.
54. Ali Z, Hila K. Disturbance observer-based control: weighted aggregated Aczel-Alsina sum product assessment based on power operators for managing fuzzy 2-tuple linguistic neural networks. *Cognit Comput.* 2025;17(1):30. <https://doi.org/10.1007/s12559-024-10371-4>.
55. Han Y, Ji Y, Qu S. ELICIT trust-driven robust consensus model in social network linguistic large-scale group decision-making. *Expert Syst Appl.* 2025;129053. <https://doi.org/10.1016/j.eswa.2025.129053>.
56. Zulqarnain RM, Wang H, Zulfiqar U, Ali R, Siddique I, Ghallab AS, *et al.* Evaluation of food waste treatment techniques using Aczel-Alsina based MAGDM model in the q-rung orthopair fuzzy soft structure. *Sci Rep.* 2025;15(1):26072. <https://doi.org/10.1038/s41598-025-09082-z>.
57. Senapati T. An Aczel-Alsina aggregation-based outranking method for multiple attribute decision-making using single-valued neutrosophic numbers. *Complex Intell Syst.* 2024;10(1):1185–99. <https://doi.org/10.1007/s40747-023-01215-z>.
58. Wang J, Tang X, Wei G. Models for multiple attribute decision-making with dual generalized single-valued neutrosophic Bonferroni mean operators. *Algorithms.* 2018 Jan 5;11(1):2–115. <https://doi.org/10.3390/a11010002>.
59. Liu P, Zhang L. Multiple criteria decision making method based on neutrosophic hesitant fuzzy Heronian mean aggregation operators. *J Intell Fuzzy Syst.* 2017 Jan 13;32(1):303–19. <https://doi.org/10.3233/JIFS-151760>.

Appendix A. List of abbreviations

- MCDM: Multi-Criteria Decision-Making
- MVRNNs: Multi-Valued Rough Neutrosophic Numbers
- MVRNAMO: Multi-Valued Rough Neutrosophic Arithmetic Mean Operator
- WMVRNAMO: Weighted Multi-Valued Rough Neutrosophic Arithmetic Mean Operator
- MVRNGMO: Multi-Valued Rough Neutrosophic Geometric Mean Operator
- WMVRNGMO: Weighted Multi-Valued Rough Neutrosophic Geometric Mean Operator
- \mathbb{A}_{MVRN} : Multi-Valued Rough Neutrosophic Arithmetic Mean Operator (in equations)
- \mathbb{A}_{MVRN}^w : Weighted Multi-Valued Rough Neutrosophic Arithmetic Mean Operator (in equations)
- \mathbb{G}_{MVRN} : Multi-Valued Rough Neutrosophic Geometric Mean Operator (in equations)
- \mathbb{G}_{MVRN}^w : Weighted Multi-Valued Rough Neutrosophic Geometric Mean Operator (in equations)
- HCNS: Hesitant Complex Neutrosophic Sets
- NS: Neutrosophic Set
- SVNNs: Single-Valued Neutrosophic Numbers
- IVNNs: Interval-valued Neutrosophic Numbers
- MVNNs: Multi-valued Neutrosophic Numbers
- MVRNNs: Multi-valued Rough Neutrosophic Numbers

نهج محايد تقريبي متعدد القيم لاتخاذ القرارات متعددة المعايير: تطبيق في اختيار المستشفيات

ك. جوماتي، ج. ديبا

كلية العلوم المتقدمة، معهد فيلور للتكنولوجيا، فيلور، تاميل نادو، الهند.

الخلاصة

تُوصف مشكلات اتخاذ القرار غالبًا بالتعقيد وعدم اليقين، مما يطرح تحديات كبيرة أمام الأفراد أو المنظمات. وغالبًا ما تعجز طرق التجميع التقليدية عن التعامل مع البيانات غير الدقيقة والمتناقضة وغير الواضحة التي تميز هذه الحالات. ولمعالجة هذه الإشكاليات، تقترح هذه الدراسة طريقة جديدة لاتخاذ القرار متعدد المعايير بالاعتماد على الأعداد النيوتروسوفية الخشنة متعددة القيم. في البداية، نقدّم القوانين التشغيلية الأساسية للأعداد النيوتروسوفية الخشنة متعددة القيم، استنادًا إلى معياري t -norm و t -conorm. بعد ذلك، نطوّر أربعة معاملات تجميع جديدة قائمة على هذه الأعداد، وهي: معامل المتوسط الحسابي للأعداد النيوتروسوفية الخشنة متعددة القيم، ومعامل المتوسط الحسابي الموزون لها، ومعامل المتوسط الهندسي لها، ومعامل المتوسط الهندسي الموزون.

الكلمات المفتاحية: معاملات التجميع، اختيار المستشفيات، اتخاذ القرار متعدد المعايير، الأعداد النيوتروسوفية الخشنة متعددة القيم، المجموعة النيوتروسوفية الخشنة، مقياس شابلي الضبابي.