Hybrid Binary Logarithm Similarity Measure for MAGDM Problems under SVNS Assessments

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Abstract: Single valued neutrosophic set is an important mathematical tool for tackling uncertainty in scientific and engineering problems because it can handle situation involving indeterminacy. In this research, we introduce new similarity measures for single valued neutrosophic sets based on binary logarithm function. We define two type of binary logarithm similarity measures and weighted binary logarithm similarity measures for single valued neutrosophic sets. Then we define hybrid binary logarithm similarity measure and weighted hybrid binary logarithm similarity measure for single valued neutrosophic sets. We prove the basic properties of the proposed measures.

Keywords: single valued neutrosophic set; binary logarithm function; similarity measure; entropy function; ideal solution; MAGDM

1 Introduction

Smarandach [1] introduced neutrosophic sets (NSs) to pave the way to deal with problems involving uncertainty, indeterminacy and inconsistency. Wang et al. [2] grounded the concept of single valued neutrosophic sets (SVNSs), a subclass of NSs to tackle engineering and scientific problems. SVNSs have been applied to solve various problems in different fields such as medical problems [3–5], decision making problems [6–18], conflict resolution [19], social problems [20–21] engineering problems [22–23], image processing problems [24–26] and so on.

The concept of similarity measure is very significant in studying almost every practical field. In the literature, few studies have addressed similarity measures for SVNSs [27–30]. Peng et al. [31] developed SVNSs based multi attribute decision making (MADM) strategy employing MABAC (Multi-Attributive Border Approximation area Comparison and similarity measure), TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution) and a new similarity measure.

Ye [32] proposed cosine similarity measure based neutrosophic multiple attribute decision making (MADM) strategy. In order to overcome some disadvantages in the definition of cosine similarity measure, Ye [33] proposed ‘improved cosine similarity measures’ based on cosine function. Biswas et al. [34] studied cosine similarity measure based MCDM with trapezoidal fuzzy neutrosophic numbers. Pramanik and Mondal [35] proposed weighted fuzzy similarity measure based on tangent function. Mondal and Pramanik [36] proposed intuitionistic fuzzy similarity measure based on tangent function. Mondal and Pramanik [37] developed tangent similarity measure of SVNSs and applied it to MADM. Ye and Fu [38] studied medical diagnosis problem using a SVNSs similarity measure based on tangent function. Can and Ozguven [39] studied a MADM problem for adjusting the proportional-integral-derivative (PID) coefficients based on neutrosophic Hamming, Euclidean, set-theoretic, Dice, and Jaccard similarity measures. Several studies [40–42] have been reported in the literature for multi-attribute group decision making (MAGDM) in neutrosophic environment. Ye [43] studied the similarity measure based on distance function of SVNSs and applied it to MAGDM. Ye [44] developed several clustering methods using distance-based similarity measures for SVNSs.
Mondal et al. [45] proposed sine hyperbolic similarity measure for solving MADM problems. Mondal et al. [46] also proposed tangent similarity measure to deal with MADM problems for interval neutrosophic environment.

Lu and Ye [47] proposed logarithmic similarity measure for interval valued fuzzy set [48] and applied it in fault diagnosis strategy.

Research gap:

MAGDM strategy using similarity measure based on binary logarithm function under single valued neutrosophic environment is yet to appear.

Research questions:

- Is it possible to define a new similarity measure between single valued neutrosophic sets using binary logarithm function?
- Is it possible to define a new entropy function for single valued neutrosophic sets for determining unknown attribute weights?
- Is it possible to develop a new MAGDM strategy based on the proposed similarity measures in single valued neutrosophic environment?

The objectives of the paper:

- To define binary logarithm similarity measures for SVNS environment and prove the basic properties.
- To define a new entropy function for determining unknown weight of attributes.
- To develop a multi-attribute group decision making model based on proposed similarity measures.
- To present a numerical example for the efficiency and effectiveness of the proposed strategy.

Having motivated from the above researches on neutrosophic similarity measures, we introduce the concept of binary logarithm similarity measures for SVNS environment. The properties of binary logarithm similarity measures are established. We also propose a new entropy function to determine unknown attribute weights. We develop a MAGDM strategy using the proposed hybrid binary logarithm similarity measures. The proposed similarity measure is applied to a MAGDM problem.

The structure of the paper is as follows. Section 2 presents basic concepts of NSs, operations on NSs, SVNSs and operations on SVNSs. Section 3 proposes binary logarithm similarity measures and weighted binary logarithm similarity measures, hybrid binary logarithm similarity measure (HBLSM), weighted hybrid binary logarithm similarity measure (WHBLSM) in SVNSs environment. Section 4 proposes a new entropy measure to calculate unknown attribute weights and proves basic properties of entropy function. Section 5 presents a MAGDM strategy based weighted hybrid binary logarithm similarity measure. Section 6 presents an illustrative example to demonstrate the applicability and feasibility of the proposed strategies. Section 7 presents a sensitivity analysis for the results of the numerical example. Section 8 conducts a comparative analysis with the other existing strategies. Section 9 presents the key contribution of the paper. Section 10 summarizes the paper and discusses future scope of research.

2 Preliminaries

In this section, the concepts of NSs, SVNSs, operations on NSs and SVNSs and binary logarithm function are outlined.

2.1 Neutrosophic set (NS)

Assume that $X$ be an universe of discourse. Then a neutrosophic sets [1] $N$ can be defined as follows:

$$N = \{I_N(x), T_N(x), F_N(x) \mid x \in X\}.$$

Here the functions $T$, $I$ and $F$ define respectively the membership degree, the indeterminacy degree, and the non-membership degree of the element $x \in X$ to the set $N$. The three functions $T$, $I$ and $F$ satisfy the following the conditions:

- $T, I, F : X \rightarrow \mathbb{I}_0^1$[0, 1][0, 1][0, 1][0, 1]
- $0 \leq \sup T_N(x) + \sup I_N(x) + \sup F_N(x) \leq 3$

For two neutrosophic sets $M = \{I_M(x), T_M(x), F_M(x) \mid x \in X\}$ and $N = \{I_N(x), T_N(x), F_N(x) \mid x \in X\}$, the two relations are defined as follows:

- $M \subseteq N$ if and only if $T_M(x) \leq T_N(x)$, $I_M(x) \geq I_N(x)$, $F_M(x) \geq F_N(x)$
- $M = N$ if and only if $T_M(x) = T_N(x)$, $I_M(x) = I_N(x)$, $F_M(x) = F_N(x)$.

2.2. Single valued Neutrosophic sets (SVNSs)

Assume that $X$ be an universe of discourse. A SVNS [2] $P$ in $X$ is formed by a truth-membership function $T_P(x)$, an indeterminacy membership function $I_P(x)$, and a falsity membership function $F_P(x)$. For each point $x \in X$, $T_P(x)$, $I_P(x)$, and $F_P(x) \in [0, 1]$.

For continuous case, a SVNS $P$ can be expressed as follows:

$$P = \{\frac{T_P(x) \cdot I_P(x) \cdot F_P(x)}{x} \mid x \in X\}.$$
For discrete case, a SVNS $P$ can be expressed as follows:

$$P = \sum_{i=1}^{n} T_P(x_i), I_P(x_i), F_P(x_i) \geq x_i \in X$$

For two SVNSs $P = \{ <x : T_P(x), I_P(x), F_P(x)> | x \in X \}$ and $Q = \{ <x : T_Q(x), I_Q(x), F_Q(x)> | x \in X \}$, some definitions are stated below:

- $P \subseteq Q$ if and only if $T_P(x) \leq T_Q(x)$, $I_P(x) \geq I_Q(x)$, and $F_P(x) \geq F_Q(x)$.
- $P \supseteq Q$ if and only if $T_P(x) \geq T_Q(x)$, $I_P(x) \leq I_Q(x)$, and $F_P(x) \leq F_Q(x)$.
- $P = Q$ if and only if $T_P(x) = T_Q(x)$, $I_P(x) = I_Q(x)$, and $F_P(x) = F_Q(x)$ for any $x \in X$.
- Complement of $P$ i.e. $P^c = \{ <x : F_P(x), 1 - I_P(x), T_P(x)> | x \in X \}$.

### 2.3. Some arithmetic operations on SVNSs

**Definition 1** [49]

Let $P = \{ T_P(x), I_P(x), F_P(x) \}$ and $Q = \{ T_Q(x), I_Q(x), F_Q(x) \}$ be any two SVNSs in a universe of discourse then arithmetic operations are stated as follows.

- $P \oplus Q = \{ T_P(x) + T_Q(x) - T_P(x)T_Q(x), I_P(x) - I_Q(x), F_P(x)F_Q(x) \}$
- $P \otimes Q = \{ T_P(x)T_Q(x), I_P(x) + I_Q(x) - I_P(x)I_Q(x), F_P(x)F_Q(x) \}$
- $\alpha P = \{ [1 - (1 - T_P(x)^\alpha)], [I_P(x)^\alpha], [F_P(x)^\alpha] \}$, $\alpha > 0$
- $(P)^c = \{ (T_P(x))^\ast, 1 - (1 - I_P(x))^\ast, 1 - (1 - F_P(x))^\ast \}$, $\alpha > 0$

### 2.4. Binary logarithm function

In mathematics, the logarithm of the form $\log x$, $x > 0$ is called binary logarithm function [50]. For example, the binary logarithm of 1 is 0, the binary logarithm of 4 is 2, the binary logarithm of 16 is 4, and the binary logarithm of 64 is 6.

### 3. Binary logarithm similarity measures for SVNSs

In this section, we define two types of binary logarithm similarity measures and their hybrid and weighted hybrid similarity measures.

3.1. Binary logarithm similarity measures of SVNSs (type-I)

**Definition 2**. Let $A = \langle x(T_A(x), I_A(x), F_A(x)) \rangle$ and $B = \langle x(T_B(x), I_B(x), F_B(x)) \rangle$ be any two SVNSs. The binary logarithm similarity measure (type-I) between SVNSs $A$ and $B$ are defined as follows:

$$\text{BL}_1(A,B) = \frac{1}{n} \sum_{i=1}^{n} \log_2 \left( 2 - \frac{1}{3} \left( |T_A(x_i) - T_B(x_i)| + |I_A(x_i) - I_B(x_i)| + |F_A(x_i) - F_B(x_i)| \right) \right)$$

(1)

**Theorem 1**. The binary logarithm similarity measure $\text{BL}_1(A,B)$ between any two SVNSs $A$ and $B$ satisfy the following properties:

- $0 \leq \text{BL}_1(A,B) \leq 1$
- $\text{BL}_1(A,B) = 1$, if and only if $A = B$
- $\text{BL}_1(A,B) = \text{BL}_1(B,A)$
- If $C$ is a SVNS in $X$ and $A \subseteq B \subseteq C$ then $\text{BL}_1(A,C) \leq \text{BL}_1(A,B)$ and $\text{BL}_1(A,C) \leq \text{BL}_1(B,C)$.

**Proof 1.**

From the definition of SVNS, we write,

$$0 \leq T_A(x) + I_A(x) + F_A(x) \leq 3$$

and

$$0 \leq T_B(x) + I_B(x) + F_B(x) \leq 3$$

Thus,

$$0 \leq |T_A(x_i) - T_B(x_i)| + |I_A(x_i) - I_B(x_i)| + |F_A(x_i) - F_B(x_i)| \leq 3$$

and

$$0 \leq \max \left( |T_A(x_i) - T_B(x_i)|, |I_A(x_i) - I_B(x_i)|, |F_A(x_i) - F_B(x_i)| \right) \leq 1$$

Hence,

$$0 \leq \text{BL}_1(A,B) \leq 1$$

**Proof 2.**

For any two SVNSs $A$ and $B$,

- $A = B$
  $$\Rightarrow T_A(x) = T_B(x), I_A(x) = I_B(x), F_A(x) = F_B(x)$$
  $$\Rightarrow |T_A(x) - T_B(x)| = 0, |I_A(x) - I_B(x)| = 0, |F_A(x) - F_B(x)| = 0$$
  $$\Rightarrow \text{BL}_1(A,B) = 1$$

Conversely, for $\text{BL}_1(A,B) = 1$, we have,

$$|T_A(x) - T_B(x)| = 0, |I_A(x) - I_B(x)| = 0, |F_A(x) - F_B(x)| = 0$$
\[ F_A(x) - F_B(x) = 0 \]
\[ \Rightarrow T_A(x) = T_B(x) \cdot I_A(x) = I_B(x) \cdot F_A(x) = F_B(x) \]
\[ \Rightarrow A = B. \]

Proof.3.

We have,\[ \left| T_A(x) - T_B(x) \right| = \left| T_B(x) - T_A(x) \right|. \]
\[ \left| I_A(x) - I_B(x) \right| = \left| I_B(x) - I_A(x) \right|. \]
\[ \left| F_A(x) - F_B(x) \right| = \left| F_B(x) - F_A(x) \right|. \]
\[ \Rightarrow \text{BL}_1(A, B) = \text{BL}_1(B, A). \]

Proof.4.

For \( A \subseteq B \subseteq C \), we have,\[ T_A(x) \leq T_B(x) \leq T_C(x), \quad I_A(x) \geq I_B(x) \geq I_C(x), \]
\[ F_A(x) \geq F_B(x) \geq F_C(x) \quad \text{for } x \in X. \]
\[ \Rightarrow \left| T_A(x) - T_B(x) \right| \leq \left| T_A(x) - T_C(x) \right|, \]
\[ \left| I_A(x) - I_B(x) \right| \leq \left| I_A(x) - I_C(x) \right|, \]
\[ \left| F_A(x) - F_B(x) \right| \leq \left| F_A(x) - F_C(x) \right|. \]
\[ \Rightarrow \text{BL}_1(A, C) \leq \text{BL}_1(A, B) \quad \text{and} \quad \text{BL}_1(A, C) \leq \text{BL}_1(B, C). \]

3.2. Binary logarithm similarity measures of SVNSs (type-II)

Definition 3. [51] Let \( A = < x(T_a(x), I_a(x), F_a(x)) > \) and \( B = < x(T_b(x), I_b(x), F_b(x)) > \) be any two SVNSs. The binary logarithm similarity measure (type-II) between SVNSs \( A \) and \( B \) are defined as follows:
\[ \text{BL}_2(A, B) = \frac{1}{n} \sum_{i=1}^{n} \log_2 \left( 2 \max \left( \frac{T_A(x_i) - T_B(x_i)}{I_A(x_i) - I_B(x_i)}, \frac{I_A(x_i) - I_B(x_i)}{F_A(x_i) - F_B(x_i)} \right) \right). \]

Theorem 2. The binary logarithm similarity measure \( \text{BL}_2(A, B) \) between any two SVNSs \( A \) and \( B \) satisfy the following properties:

P1. \( 0 \leq \text{BL}_2(A, B) \leq 1 \)
P2. \( \text{BL}_2(A, B) = 1 \) if and only if \( A = B \)
P3. \( \text{BL}_2(A, B) = \text{BL}_2(B, A) \)
P4. If \( C \) is a SVNS in \( X \) and \( A \subseteq C \subseteq C \), then \( \text{BL}_2(A, C) \leq \text{BL}_2(A, B) \) and \( \text{BL}_2(A, C) \leq \text{BL}_2(B, C) \).

Proof.

Proofs of the properties are shown in [51].

3.3. Weighted binary logarithm similarity measures of SVNSs for type-I

Definition 4. Let \( A = < x(T_a(x), I_a(x), F_a(x)) > \) and \( B = < x(T_b(x), I_b(x), F_b(x)) > \) be any two SVNSs. Then the weighted binary logarithm similarity measure for type-I between SVNSs \( A \) and \( B \) are defined as follows:
\[ \text{BL}_1^w(A, B) = \sum_{i=1}^{n} w_i \log_2 \left( 2 \left( \frac{T_A(x_i) - T_B(x_i)}{I_A(x_i) - I_B(x_i)}, \frac{I_A(x_i) - I_B(x_i)}{F_A(x_i) - F_B(x_i)} \right) \right). \]

Here, \( 0 \leq w_i \leq 1 \) and \( \sum_{i=1}^{n} w_i = 1 \).

Theorem 3. The weighted binary logarithm similarity measures \( \text{BL}_1^w(A, B) \) between SVNSs \( A \) and \( B \) satisfy the following properties:
P1. \( 0 \leq \text{BL}_1^w(A, B) \leq 1 \)
P2. \( \text{BL}_1^w(A, B) = 1 \) if and only if \( A = B \)
P3. \( \text{BL}_1^w(A, B) = \text{BL}_1^w(B, A) \)
P4. If \( C \) is a SVNS in \( X \) and \( A \subseteq B \subseteq C \), then \( \text{BL}_1^w(A, C) \leq \text{BL}_1^w(A, B) \) and \( \text{BL}_1^w(A, C) \leq \text{BL}_1^w(B, C) \).

Proof.

From the definition of SVNSs \( A \) and \( B \), we write,
\[ 0 \leq T_A(x) + I_B(x) \leq F_B(x) \leq 3 \]
\[ 0 \leq T_B(x) + I_B(x) \leq F_B(x) \leq 3 \]
\[ \Rightarrow 0 \leq \left| T_A(x) - T_B(x) \right|, \left| I_A(x) - I_B(x) \right|, \left| F_A(x) - F_B(x) \right| \leq 1 \]
\[ 0 \leq \left| T_A(x) - T_B(x) \right|, \left| I_A(x) - I_B(x) \right|, \left| F_A(x) - F_B(x) \right| \leq 3 \]
\[ \Rightarrow 0 \leq \text{BL}_1^w(A, B) \leq 1 \quad \text{since,} \quad \sum_{i=1}^{n} w_i = 1. \]

Proof 2.

For any two SVNSs \( A \) and \( B \) if \( A = B \), then we have,\[ T_A(x) = T_B(x), \quad I_A(x) = I_B(x), \quad F_A(x) = F_B(x) \]
\[ \Rightarrow \left| T_A(x) - T_B(x) \right| = 0, \left| I_A(x) - I_B(x) \right| = 0, \left| F_A(x) - F_B(x) \right| = 0. \]
\[ \implies \text{BL}^i_t(A, B) = 1, \quad (t = 1, 2), \text{ since } \sum_{i=1}^{n} w_i = 1. \]

Conversely, for \( \text{BL}^i_t(A, B) = 1 \), we have,
\[ |T_i(x) - T_j(x)| = 0, \quad |I_i(x) - I_j(x)| = 0, \quad |F_i(x) - F_j(x)| = 0, \]
\[ T_i(x) = T_j(x), \quad I_i(x) = I_j(x), \quad F_i(x) = F_j(x) \]
\[ A = B, \text{ since } \sum_{i=1}^{n} w_i = 1. \]

**Proof 3.**

For any two SVNSs \( A \) and \( B \), we have,
\[ |T_i(x) - T_j(x)| = |T_i(x) - T_k(x)|, \]
\[ |I_i(x) - I_j(x)| = |I_i(x) - I_k(x)|, \]
\[ |F_i(x) - F_j(x)| = |F_i(x) - F_k(x)| \]
\[ \implies \text{BL}^i_t(A, B) = \text{BL}^i_t(B, A) \text{ for.} \]

**Proof 4.**

For \( A \subseteq B \subseteq C \), we have,
\[ T_i(x) \leq T_i(x) \leq T_i(x), \quad I_i(x) \leq I_i(x) \leq I_i(x), \]
\[ F_i(x) \leq F_i(x) \leq F_i(x) \text{ for } x \in X, \]
\[ \implies |T_i(x) - T_j(x)| \leq |T_i(x) - T_k(x)|, \]
\[ |I_i(x) - I_j(x)| \leq |I_i(x) - I_k(x)|, \]
\[ |F_i(x) - F_j(x)| \leq |F_i(x) - F_k(x)| \]
\[ \implies \text{BL}^i_t(A, C) \leq \text{BL}^i_t(A, B) \text{ and } \text{BL}^i_t(A, C) \leq \text{BL}^i_t(B, C) \]
\[ \text{since } \sum_{i=1}^{n} w_i = 1. \]

**3.4. Weighted binary logarithm similarity measures of SVNSs for type-II**

**Definition 5.** [51] Let \( A = <x(T_i(x)), I_i(x), F_i(x)> \) and \( B = <x(T_j(x)), I_j(x), F_j(x)> \) be any two SVNSs. Then the weighted binary logarithm similarity measure (type-II between SVNSs \( A \) and \( B \) is defined as follows:

\[ \text{BL}^*_t(A, B) = \sum_{i=1}^{n} w_i \log_2 \left\{ 2 - \max \left\{ \frac{|T_i(x) - T_j(x)|}{|I_i(x) - I_j(x)|}, \frac{|I_i(x) - I_j(x)|}{|F_i(x) - F_j(x)|}, \frac{|F_i(x) - F_j(x)|}{|T_i(x) - T_j(x)|} \right\} \right\} \]

\[ \text{(5)} \]

Here, \( 0 \leq w_i \leq 1 \) and \( \sum_{i=1}^{n} w_i = 1. \)

**Proof.**

For proof, see [51].

**3.3. Hybrid binary logarithm similarity measures (HBLSM) for SVNSs**

**Definition 6.** Let \( A = <x(T_i(x)), I_i(x), F_i(x)> \) and \( B = <x(T_j(x)), I_j(x), F_j(x)> \) be any two SVNSs. The hybrid binary logarithm similarity measure between SVNSs \( A \) and \( B \) is defined as follows:

\[ \text{BL}_{H_{BL}}(A, B) = \sum_{i=1}^{n} w_i \log_2 \left\{ 2 - \max \left\{ \frac{|T_i(x) - T_j(x)|}{|I_i(x) - I_j(x)|}, \frac{|I_i(x) - I_j(x)|}{|F_i(x) - F_j(x)|}, \frac{|F_i(x) - F_j(x)|}{|T_i(x) - T_j(x)|} \right\} \right\} \]

\[ \text{(4)} \]

Here, \( 0 \leq w_i \leq 1 \) and \( \sum_{i=1}^{n} w_i = 1. \)

**Theorem 4.** The hybrid binary logarithm similarity measure \( \text{BL}_{H_{BL}}(A, B) \) between any two SVNSs \( A \) and \( B \) satisfy the following properties:

P1. \( 0 \leq \text{BL}_{H_{BL}}(A, B) \leq 1 \)

P2. \( \text{BL}_{H_{BL}}(A, B) = 1 \) if and only if \( A = B \)

P3. \( \text{BL}_{H_{BL}}(A, B) = \text{BL}_{H_{BL}}(B, A) \)

P4. If \( C \) is a SVNS in \( X \) and \( A \subseteq B \subseteq C \) then \( \text{BL}_{H_{BL}}(A, C) \leq \text{BL}_{H_{BL}}(B, A) \)

and \( \text{BL}_{H_{BL}}(A, C) \leq \text{BL}_{H_{BL}}(B, C) \).

**Proof 1.**

From the definition of SVNS, we write,
\[ 0 \leq T_i(x) + I_i(x) + F_i(x) \leq 3 \text{ and } 0 \leq T_j(x) + I_j(x) + F_j(x) \leq 3 \]
\[ \Rightarrow 0 \leq \max \left\{ \left| p_a(x) - T_b(x) \right|, \left| p_b(x) - T_a(x) \right| \right\} \leq 1 \]

\[ \Rightarrow \left| p_a(x) - T_b(x) \right| \leq \left| p_a(x) - I_b(x) \right| + \left| I_a(x) - I_b(x) \right| \leq 3 \]

\[ \Rightarrow 0 \leq \left| p_a(x) - T_b(x) \right| \leq 3 \]

\[ \Rightarrow 0 \leq BL_{Hyb}(A, B) \leq 1. \]

**Proof 2.**

For any two SVNSs \( A \) and \( B \), for \( A = B \), we have,

\[ T_a(x) = T_b(x), \quad I_a(x) = I_b(x), \quad F_a(x) = F_b(x) \]

\[ \Rightarrow \left| T_a(x) - T_b(x) \right| = 0, \quad \left| I_a(x) - I_b(x) \right| = 0, \quad \left| F_a(x) - F_b(x) \right| = 0 \]

\[ \Rightarrow BL_{Hyb}(A, B) = 1. \]

Conversely, for \( BL_{Hyb}(A, B) = 1 \), we have,

\[ \left| T_a(x) - T_b(x) \right| = 0, \quad \left| I_a(x) - I_b(x) \right| = 0, \quad \left| F_a(x) - F_b(x) \right| = 0 \]

\[ \Rightarrow T_a(x) = T_b(x), \quad I_a(x) = I_b(x), \quad F_a(x) = F_b(x) \]

\[ \Rightarrow A = B. \]

**Proof 3.**

For any two SVNSs \( A \) and \( B \), we have,

\[ \left| T_a(x) - T_b(x) \right| = \left| T_a(x) - T_b(x) \right|, \quad \left| I_a(x) - I_b(x) \right| = \left| I_a(x) - I_b(x) \right|, \quad \left| F_a(x) - F_b(x) \right| = \left| F_a(x) - F_b(x) \right| \]

\[ \Rightarrow BL_{Hyb}(A, B) = BL_{Hyb}(B, A). \]

**Proof 4.**

For \( A \subseteq B \subseteq C \), we have,

\[ T_a(x) \leq T_b(x) \leq T_c(x), \quad I_a(x) \geq I_b(x) \geq I_c(x), \quad F_a(x) \leq F_b(x) \leq F_c(x) \]

\[ \Rightarrow \left| T_a(x) - T_b(x) \right| \leq \left| T_a(x) - T_c(x) \right|, \quad \left| I_a(x) - I_b(x) \right| \geq \left| I_a(x) - I_c(x) \right|, \quad \left| F_a(x) - F_b(x) \right| \leq \left| F_a(x) - F_c(x) \right| \]

\[ \Rightarrow BL_{Hyb}(A, C) \leq BL_{Hyb}(A, B) \]

and \( BL_{Hyb}(A, C) \leq BL_{Hyb}(B, C). \)

**3.4. Weighted hybrid binary logarithm similarity measures (WHBLSM) for SVNSs**

**Definition 7.** Let \( A = \langle x(T_a(x), I_a(x), F_a(x)) \rangle \) and \( B = \langle x(T_b(x), I_b(x), F_b(x)) \rangle \) be any two SVNSs. The weighted hybrid binary logarithm similarity measure between SVNSs \( A \) and \( B \) is defined as follows:

\[ BL_{wHyb}(A, B) = \begin{cases} \lambda \sum_{i=1}^{n} w_i \log_2 \left( 2 - \frac{1}{3} \left[ \left| T_a(x_i) - T_b(x_i) \right| + \left| I_a(x_i) - I_b(x_i) \right| \right] \right) \\ + (1 - \lambda) \sum_{i=1}^{n} w_i \log_2 \left( 2 - \max \left[ \left| I_a(x_i) - I_b(x_i) \right|, \left| F_a(x_i) - F_b(x_i) \right| \right] \right) \end{cases} \]

Here, \( 0 \leq \lambda \leq 1. \)

**Theorem 5.** The weighted hybrid binary logarithm similarity measure \( BL_{wHyb}(A, B) \) between any two SVNSs \( A \) and \( B \) satisfies the following properties:

**P1.** \( 0 \leq BL_{wHyb}(A, B) \leq 1 \)

**P2.** \( BL_{wHyb}(A, B) = 1 \), if and only if \( A = B \)

**P3.** \( BL_{wHyb}(A, B) = BL_{wHyb}(B, A) \)

**P4.** If \( C \) is a SVNS in \( X \) and \( A \subseteq B \subseteq C \), then \( BL_{wHyb}(A, C) \leq BL_{wHyb}(A, B) \)

and \( BL_{wHyb}(A, C) \leq BL_{wHyb}(B, C). \)

**Proof 1.**

From the definition of SVNS, we write,

\[ 0 \leq T_a(x) + I_a(x) + F_a(x) \leq 3 \]

\[ 0 \leq T_b(x) + I_b(x) + F_b(x) \leq 3 \]

\[ \Rightarrow 0 \leq \max \left[ \left| T_a(x_i) - T_b(x_i) \right| + \left| I_a(x_i) - I_b(x_i) \right| \right] \leq 1 \]

\[ \Rightarrow 0 \leq \left| T_a(x_i) - T_b(x_i) \right| + \left| I_a(x_i) - I_b(x_i) \right| \leq 3 \]

\[ \Rightarrow 0 \leq BL_{wHyb}(A, B) \leq 1. \]

**Proof 2.**

For any two SVNSs \( A \) and \( B \),
for $A = B$, we have,
\[
T_A(x) = T_B(x), I_A(x) = I_B(x), F_A(x) = F_B(x)
\]
\[
| \mathcal{T}_A(x) - \mathcal{T}_B(x) | = 0, | I_A(x) - I_B(x) | = 0.
\]
\[
| F_A(x) - F_B(x) | = 0.
\]
\[
\implies BL_{wHyb}(A, B) = 1.
\]

Conversely,
for $BL_{wHyb}(A, B) = 1$, we have,
\[
T_A(x) - T_B(x) = 0, I_A(x) - I_B(x) = 0,
\]
\[
F_A(x) - F_B(x) = 0.
\]
\[
\implies T_A(x) = T_B(x), I_A(x) = I_B(x), F_A(x) = F_B(x).
\]
\[
\implies A = B.
\]

**Proof 3.**

For any two SVNSs $A$ and $B$, we have,
\[
T_A(x) - T_B(x) = | T_A(x) - T_B(x) |,
\]
\[
I_A(x) - I_B(x) = | I_A(x) - I_B(x) |,
\]
\[
F_A(x) - F_B(x) = | F_A(x) - F_B(x) |.
\]
\[
\implies BL_{wHyb}(A, B) = BL_{wHyb}(B, A).
\]

**Proof 4.**

For $A \subseteq B \subseteq C$, we have,
\[
T_A(x) \leq T_B(x) \leq T_C(x), I_A(x) \geq I_B(x) \geq I_C(x),
\]
\[
F_A(x) \geq F_B(x) \geq F_C(x)
\]
\[
\text{for all } x \in X.
\]
\[
| T_A(x) - T_B(x) | \leq | T_A(x) - T_C(x) |,
\]
\[
| I_A(x) - I_B(x) | \leq | I_A(x) - I_C(x) |,
\]
\[
| F_A(x) - F_B(x) | \leq | F_A(x) - F_C(x) |.
\]
\[
\implies BL_{wHyb}(A, C) \leq BL_{wHyb}(A, B) \text{ and } BL_{wHyb}(A, C) \leq BL_{wHyb}(B, C).
\]

**4. A new entropy measure for SVNSs**

Entropy strategy [52] is an important contribution for determining indeterminate information. Zhang et al. [53] introduced the fuzzy entropy. Vlachos and Sergiadis [54] proposed entropy function for intuitionistic fuzzy sets. Majumder and Samanta [55] developed some entropy measures for SVNSs. When attribute weights are completely unknown to decision makers, the entropy measure is used to calculate attribute weights. In this paper, we define an entropy measure for determining unknown attribute weights.

**Definition 8.** The entropy function of a SVNS $P = \{T^p_i(x), I^p_i(x), F^p_i(x)\} (i = 1, 2, ..., m; j = 1, 2, ..., n)$ is defined as follows:
\[
E_j(P) = 1 - \frac{1}{n} \sum_{i=1}^{m} \left( T^p_i(x) + F^p_i(x) \right) \left( 1 - 2T^p_i(x) \right)^2
\]
\[
(7)
\]
\[
w_j = \frac{1 - E_j(P)}{n - \sum_{j=1}^{n} E_j(P)}
\]

Here, $\sum_{i=1}^{m} w_j = 1$

**Theorem 6.** The entropy function $E_j(P)$ satisfies the following properties:

- **P1.** $E_j(P) = 0$, if $T_j = 1, F_j = I_j = 0$.
- **P2.** $E_j(P) = 1$, if $T_{ij} = 0.5, 0.5, 0.5, 0.5$.
- **P3.** $E_j(P) = E_j(Q)$, if $T^p_i + F^p_i \leq T^q_i + F^q_i$.
- **P4.** $E_j(P) = E_j(P^r)$.

**Proof 1.**
\[
T_y = 1, F_y = I_y = 0
\]
\[
\implies E_j(P) = 1 - \frac{1}{n} \sum_{i=1}^{m} \left( (0.5 + 0.5) \times 0 \right) = 1 - 0 = 1
\]

**Proof 2.**
\[
\tilde{T}_{ij} , I_{ij} , F_{ij} = \langle 0.5, 0.5, 0.5 \rangle.
\]
\[
\implies E_j(P) = 1 - \frac{1}{n} \sum_{i=1}^{m} \left( (0.5 + 0.5) \times 0 \right) = 1 - 0 = 1
\]

**Proof 3.**
\[
T^p_i + F^p_i \leq T^q_i + F^q_i, I^p_i \geq I^q_i
\]
\[
\implies \sum_{i=1}^{m} \left( T^p_i + F^p_i \right) \left( 1 - 2T^p_i \right)^2 \leq \sum_{i=1}^{m} \left( T^q_i + F^q_i \right) \left( 1 - 2T^q_i \right)^2
\]
\[
\implies \sum_{i=1}^{m} \left( T^p_i + F^p_i \right) \left( 1 - 2T^p_i \right)^2 \leq \sum_{i=1}^{m} \left( T^q_i + F^q_i \right) \left( 1 - 2T^q_i \right)^2
\]
\[
\implies 1 - \frac{1}{n} \sum_{i=1}^{m} \left( T^p_i + F^p_i \right) \left( 1 - 2T^p_i \right)^2 \geq 1 - \frac{1}{n} \sum_{i=1}^{m} \left( T^q_i + F^q_i \right) \left( 1 - 2T^q_i \right)^2
\]
\[
\implies E_j(P) \geq E_j(Q).
\]

**Proof 4.**
\[
\text{Since } \tilde{T}_{ij}, I_{ij}, F_{ij} = \langle F_{ij} , 1-I_{ij}, T_{ij} \rangle, \text{ we have}
\]
\[
E_j(P) = E_j(P^r) .
\]
5. MAGDM strategy based on weighted hybrid binary logarithm similarity measure for SVNSs

Assume that \((P_1, P_2, ..., P_m)\) be the alternatives, \((C_1, C_2, ..., C_n)\) be the attributes of each alternative, and \{\(D_1, D_2, ..., D_t\)\} be the decision makers. Decision makers provide the rating of alternatives based on the predefined attribute. Each decision maker constructs a neutrosophic decision matrix associated with the attributes based on each attribute shown in Equation (9). Using the following steps, we present the MAGDM strategy (see figure 1) based on weighted hybrid binary logarithm similarity measure (WHBLSM).

**Step 1:** Determine the relation between the alternatives and the attributes

At first, each decision maker prepares decision matrix. The relation between alternatives \(P_i\) \((i = 1, 2, ..., m)\) and the attribute \(C_j\) \((j = 1, 2, ..., n)\) corresponding to each decision maker is presented in the Equation (9).

\[
D_t[P | C] = \begin{pmatrix}
C_1 \\
P_1 \left[ \begin{array}{c} T_{D_1}^{P_1}, I_{D_1}^{P_1}, F_{D_1}^{P_1} \\ T_{D_2}^{P_1}, I_{D_2}^{P_1}, F_{D_2}^{P_1} \\ \vdots \\ T_{D_m}^{P_1}, I_{D_m}^{P_1}, F_{D_m}^{P_1} \end{array} \right] \\
C_2 \\
P_2 \left[ \begin{array}{c} T_{D_1}^{P_2}, I_{D_1}^{P_2}, F_{D_1}^{P_2} \\ T_{D_2}^{P_2}, I_{D_2}^{P_2}, F_{D_2}^{P_2} \\ \vdots \\ T_{D_m}^{P_2}, I_{D_m}^{P_2}, F_{D_m}^{P_2} \end{array} \right] \\
\vdots \\
P_m \left[ \begin{array}{c} T_{D_1}^{P_m}, I_{D_1}^{P_m}, F_{D_1}^{P_m} \\ T_{D_2}^{P_m}, I_{D_2}^{P_m}, F_{D_2}^{P_m} \\ \vdots \\ T_{D_m}^{P_m}, I_{D_m}^{P_m}, F_{D_m}^{P_m} \end{array} \right]
\end{pmatrix}
\] (9)

Here, \(\{T_{D_i}^{P_i}, I_{D_i}^{P_i}, F_{D_i}^{P_i}\}\) \((i = 1, 2, ..., m; j = 1, 2, ..., n)\) is the single valued neutrosophic rating value of the alternative \(P_i\) with respect to the attribute \(C_j\) corresponding to the decision maker \(D_t\).

**Step 2:** Determine the core decision matrix

We form a new decision matrix, called core decision matrix to combine all the decision maker’s opinions into a group opinion. Core decision matrix minimizes the biasness which is imposed by different decision makers and hence credibility to the final decision increases. The core decision matrix is presented in Equation (10).

\[
D[P | C] = \begin{pmatrix}
C_1 \\
P_1 \left[ \begin{array}{c} \bigtriangledown (T_{D_1}^{P_1}, I_{D_1}^{P_1}, F_{D_1}^{P_1}) \\ \bigtriangledown (T_{D_2}^{P_1}, I_{D_2}^{P_1}, F_{D_2}^{P_1}) \\ \vdots \\ \bigtriangledown (T_{D_m}^{P_1}, I_{D_m}^{P_1}, F_{D_m}^{P_1}) \end{array} \right] \\
C_2 \\
P_2 \left[ \begin{array}{c} \bigtriangledown (T_{D_1}^{P_2}, I_{D_1}^{P_2}, F_{D_1}^{P_2}) \\ \bigtriangledown (T_{D_2}^{P_2}, I_{D_2}^{P_2}, F_{D_2}^{P_2}) \\ \vdots \\ \bigtriangledown (T_{D_m}^{P_2}, I_{D_m}^{P_2}, F_{D_m}^{P_2}) \end{array} \right] \\
\vdots \\
P_m \left[ \begin{array}{c} \bigtriangledown (T_{D_1}^{P_m}, I_{D_1}^{P_m}, F_{D_1}^{P_m}) \\ \bigtriangledown (T_{D_2}^{P_m}, I_{D_2}^{P_m}, F_{D_2}^{P_m}) \\ \vdots \\ \bigtriangledown (T_{D_m}^{P_m}, I_{D_m}^{P_m}, F_{D_m}^{P_m}) \end{array} \right]
\end{pmatrix}
\] (10)

**Step 3:** Determine the ideal solution

The evaluation of attributes can be categorized into benefit attribute and cost attribute. An ideal alternative can be determined by using a maximum operator for the benefit attributes and a minimum operator for the cost attributes for determining the best value of each attribute among all the alternatives. An ideal alternative [42] is presented as follows:

\[
P^* = \{C_1^*, C_2^*, ..., C_n^*\}
\]

where the benefit attribute is

\[
C_j = \left\{ \max_{i} T_{C_j}^{(P_i)}, \min_{i} I_{C_j}^{(P_i)} \right\}
\] (11)

and the cost attribute is

\[
C_j = \left\{ \min_{i} T_{C_j}^{(P_i)}, \max_{i} I_{C_j}^{(P_i)} \right\}
\] (12)

**Step 4:** Determine the attribute weights

Using Equation (8), determine the weights of the attribute.

**Step 5:** Determine the WHBLSM values

Using Equation (6), calculate the weighted similarity measures for each alternative.

**Step 6:** Ranking the priority

All the alternatives are preference ranked based on the decreasing order of calculated measure values. The highest value reflects the best alternative.

**Step 7:** End.

6. An illustrative example

Suppose that a state government wants to construct an eco-tourism park for the development of state tourism and especially for mental refreshment of children. After initial screening, three potential spots namely, spot-1 \(P_1\), spot-2 \(P_2\), and spot-3 \(P_3\) remain for further selection. A team
of three decision makers, namely, \( D_1 \), \( D_2 \), and \( D_3 \) has been constructed for selecting the most suitable spot with respect to the following attributes:

- Ecology (\( C_1 \)),
- Costs (\( C_2 \)),
- Technical facility (\( C_3 \)),
- Transport (\( C_4 \)),
- Risk factors (\( C_5 \)).

The steps of decision-making strategy to select the best potential spot to construct an eco-tourism park based on the proposed strategy are stated below:

6.1. Steps of MAGDM strategy

We present MAGDM strategy based on the proposed WHBLSM using the following steps.

Step 1: Determine the relation between alternatives and attributes

The relation between alternatives \( P_1 \), \( P_2 \) and \( P_3 \) and the attribute set \( \{ C_1, C_2, C_3, C_4, C_5 \} \) corresponding to the set of decision makers \( \{ D_1, D_2, D_3 \} \) are presented in Equations (13), (14), and (15).

\[
D_1[P | C] = \begin{pmatrix}
C_1 & C_2 & C_3 & C_4 & C_5 \\
0.7 & 0.7 & 0.8 & 0.7 & 0.6 \\
0.4 & 0.4 & 0.1 & 0.2 & 0.5 \\
0.4 & 0.5 & 0.6 & 0.7 & 0.4 \\
0.3 & 0.2 & 0.2 & 0.3 & 0.3 \\
0.6 & 0.5 & 0.2 & 0.3 & 0.4 \\
0.4 & 0.8 & 0.5 & 0.5 & 0.7 \\
0.2 & 0.4 & 0.2 & 0.3 & 0.4 \\
0.3 & 0.3 & 0.4 & 0.2 & 0.2 \\
\end{pmatrix}
\]

\[
D_2[P | C] = \begin{pmatrix}
C_1 & C_2 & C_3 & C_4 & C_5 \\
0.5 & 0.7 & 0.8 & 0.5 & 0.5 \\
0.2 & 0.4 & 0.2 & 0.2 & 0.5 \\
0.3 & 0.4 & 0.2 & 0.2 & 0.4 \\
0.5 & 0.5 & 0.5 & 0.8 & 0.4 \\
0.4 & 0.2 & 0.3 & 0.3 & 0.1 \\
0.4 & 0.4 & 0.3 & 0.3 & 0.4 \\
0.4 & 0.8 & 0.5 & 0.7 & 0.7 \\
0.2 & 0.2 & 0.3 & 0.2 & 0.4 \\
0.5 & 0.2 & 0.3 & 0.2 & 0.2 \\
\end{pmatrix}
\]

\[
D_3[P | C] = \begin{pmatrix}
C_1 & C_2 & C_3 & C_4 & C_5 \\
0.7 & 0.8 & 0.6 & 0.7 & 0.5 \\
0.4 & 0.2 & 0.3 & 0.2 & 0.6 \\
0.3 & 0.1 & 0.3 & 0.5 & 0.5 \\
0.6 & 0.5 & 0.7 & 0.5 & 0.3 \\
0.2 & 0.1 & 0.4 & 0.3 & 0.4 \\
0.3 & 0.3 & 0.4 & 0.2 & 0.4 \\
0.6 & 0.6 & 0.5 & 0.7 & 0.5 \\
0.2 & 0.4 & 0.3 & 0.4 & 0.6 \\
0.3 & 0.2 & 0.3 & 0.2 & 0.4 \\
\end{pmatrix}
\]

(15)

\[
D_1[P | C] = \begin{pmatrix}
C_1 & C_2 & C_3 & C_4 & C_5 \\
0.7 & 0.8 & 0.6 & 0.7 & 0.5 \\
0.4 & 0.2 & 0.3 & 0.2 & 0.6 \\
0.3 & 0.1 & 0.3 & 0.5 & 0.5 \\
0.6 & 0.5 & 0.7 & 0.5 & 0.3 \\
0.2 & 0.1 & 0.4 & 0.3 & 0.4 \\
0.3 & 0.3 & 0.4 & 0.2 & 0.4 \\
0.6 & 0.6 & 0.5 & 0.7 & 0.5 \\
0.2 & 0.4 & 0.3 & 0.4 & 0.6 \\
0.3 & 0.2 & 0.3 & 0.2 & 0.4 \\
\end{pmatrix}
\]

(16)

Step 2: Determine the core decision matrix

Using Equation (10), we construct the core decision matrix for all decision makers shown in Equation (16).

Step 3: Determine the ideal solution

Here, \( C_3 \) and \( C_4 \) denote benefit attributes and \( C_1 \), \( C_2 \) and \( C_5 \) denote cost attributes. Using Equations (11) and (12), we calculate the ideal solutions as follows:

\[
P^{*} = \{ (0.984, 0.989, 0.989, 0.956, 0.942),
(0.324, 0.324, 0.184, 0.203, 0.203),
(0.938, 0.996, 0.979, 0.989, 0.908),
(0.292, 0.162, 0.292, 0.304, 0.232),
(0.420, 0.395, 0.292, 0.334, 0.404),
(0.949, 0.994, 0.956, 0.984, 0.984),
(0.203, 0.203, 0.334, 0.255, 0.420),
(0.359, 0.232, 0.203, 0.203, 0.255)\}
\]

Step 4: Determine the attribute weights

Using Equation (8), we calculate the attribute weights as follows:

\[
[w_1, w_2, w_3, w_4, w_5] = [0.1680, 0.3300, 0.2285, 0.2485, 0.0250]
\]

Step 5: Determine the weighted hybrid binary logarithm similarity measures

Using Equation (6), we calculate similarity values for alternatives shown in Table 1.
Step 6: Ranking the alternatives

Ranking order of alternatives is prepared as the descending order of similarity values. Highest value indicates the best alternative. Ranking results are shown in Table 1 for different values of $\lambda$.

Step 7. End.

7. Sensitivity analysis

In this section, we discuss the variation of ranking results (see Table 1) for different values of $\lambda$. From the results shown in Tables 1, we observe that the proposed strategy provides the same ranking order for different values of $\lambda$.

8. Comparison analysis

In this section, we solve the problem with different existing strategies [33, 37, 38, 56]. Outcomes are furnished in the Table 2 and figure 2.

9. Contributions of the proposed strategy

- We propose two types of binary logarithm similarity measures and their hybrid similarity measure for SVNS environment. We have proved their basic properties.
- To calculate unknown weights structure of attributes in SVNS environment, we have proposed a new entropy function.
- We develop a decision making strategy based on the proposed weighted hybrid binary logarithm similarity measure (WHBLSM).
- We have solved an illustrative example to show the feasibility, applicability, and effectiveness of the proposed strategy.

10. Conclusion

Conclusions in the paper are concise as follows:

1. We have proposed hybrid binary logarithm similarity measure and weighted hybrid binary logarithm similarity measure for dealing indeterminacy in decision making situation.
2. We have defined a new entropy function to determine unknown attribute weights.
3. We have developed a new MAGDM strategy based on the proposed weighted hybrid binary logarithm similarity measure.
4. We have presented a numerical example to illustrate the proposed strategy.
5. We have conducted a sensitivity analysis
6. We have presented comparative analyses between the obtained results from the proposed strategies and different existing strategies in the literature. The proposed weighted hybrid binary logarithm similarity measure can be applied to solve MAGDM problems in clustering analysis, pattern recognition, personnel selection, etc.
7. Future research can be continued to investigate the proposed similarity measures in neutrosophic hybrid environment for tackling uncertainty, inconsistency and indeterminacy in decision making. The concept of the paper can be applied in practical decision-making, supply chain management, data mining, cluster analysis, teacher selection etc.

| Table 1 Ranking order for different values of $\lambda$. |
|---|---|---|
| Similarity measures | ($\lambda$) | Measure values |
| $\text{BL}_{wHyb}(P^*, P_i)$ | 0.10 | $\text{BL}_{wHyb}(P^*, P_1) = 0.9426$; $\text{BL}_{wHyb}(P^*, P_2) = 0.9233$; $\text{BL}_{wHyb}(P^*, P_3) = 0.9101$ |
| $\text{BL}_{wHyb}(P^*, P_i)$ | 0.25 | $\text{BL}_{wHyb}(P^*, P_1) = 0.9479$; $\text{BL}_{wHyb}(P^*, P_2) = 0.9296$; $\text{BL}_{wHyb}(P^*, P_3) = 0.9153$ |
| $\text{BL}_{wHyb}(P^*, P_i)$ | 0.40 | $\text{BL}_{wHyb}(P^*, P_1) = 0.9532$; $\text{BL}_{wHyb}(P^*, P_2) = 0.9357$; $\text{BL}_{wHyb}(P^*, P_3) = 0.9207$ |
| $\text{BL}_{wHyb}(P^*, P_i)$ | 0.55 | $\text{BL}_{wHyb}(P^*, P_1) = 0.9585$; $\text{BL}_{wHyb}(P^*, P_2) = 0.9419$; $\text{BL}_{wHyb}(P^*, P_3) = 0.9260$ |
| $\text{BL}_{wHyb}(P^*, P_i)$ | 0.70 | $\text{BL}_{wHyb}(P^*, P_1) = 0.9638$; $\text{BL}_{wHyb}(P^*, P_2) = 0.9482$; $\text{BL}_{wHyb}(P^*, P_3) = 0.9313$ |
| $\text{BL}_{wHyb}(P^*, P_i)$ | 0.90 | $\text{BL}_{wHyb}(P^*, P_1) = 0.9708$; $\text{BL}_{wHyb}(P^*, P_2) = 0.9565$; $\text{BL}_{wHyb}(P^*, P_3) = 0.9384$ |

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Table 2 Ranking order for different existing strategies

<table>
<thead>
<tr>
<th>Similarity measures</th>
<th>Measure values for $P_1$, $P_2$ and $P_3$</th>
<th>Ranking order</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mondal and Pramanik [37]</td>
<td>0.8901, 0.8679, 0.8093</td>
<td>$P_1 &gt; P_2 &gt; P_3$</td>
</tr>
<tr>
<td>Ye [33]</td>
<td>0.8409, 0.8189, 0.7766</td>
<td>$P_1 &gt; P_2 &gt; P_3$</td>
</tr>
<tr>
<td>Biswas et al. [56] ($\lambda=0.55$)</td>
<td>0.9511, 0.9219, 0.9007</td>
<td>$P_1 &gt; P_2 &gt; P_3$</td>
</tr>
<tr>
<td>Ye and Fu [38]</td>
<td>0.9161, 0.8758, 0.7900</td>
<td>$P_1 &gt; P_2 &gt; P_3$</td>
</tr>
<tr>
<td>Proposed strategy ($\lambda=0.55$)</td>
<td>0.9585, 0.9419, 0.9260</td>
<td>$P_1 &gt; P_2 &gt; P_3$</td>
</tr>
</tbody>
</table>

Fig. 1: Decision making phases of the proposed approach
References


[40] K. Mondal, S. Pramanik. Multi-criteria group decision making approach for teacher recruitment in higher education.


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