A New Single-valued Neutrosophic Distance for TOPSIS, MABAC and New Similarity Measure in Multi-Attribute Decision-Making

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***Abstract*—The aim of this paper is to define a new distance measure and apply it in three decision-making methods. First of all, we use single-valued neutrosophic numbers to describe the decision-making information, and proposes a new single-valued neutrosophic distance based on Hamming distance and Hausdorff distance. According to this new distance, a new similarity measure is initiated. Then we introduce three methods, which are TOPSIS, MABAC and similarity measure, to solve multi-attribute decision-making problem. Among these methods, the combined weight is obtained by both objective weight and subjective weight. After that, a numerical example is applied to figure out a ideal solution. Finally, we compare this result with other papers and discuss the effectiveness and reasonability.**

***Index Terms*—Single-valued Neutrosophic Number; TOPSIS; MABAC; Similarity Measure ; Multi-Attribute Decision-Making.**

I. Introduction

DECISION-MAKING means selecting the best alternatives from the feasible alternatives. With the development of science, decision-making extends from the single attribute to multiple attributes. In order to make a proper decision-making and apply decision-making in the actual situation, Wang et al. [1]proposed a single-valued neutrosophic set (SVNS) and also introduced the set-theoretic operators of SVNSs. Sodenkamp et al. [2]developed a novel approach that utilizes single-valued neutrosophic sets (NSs) to process independent multi-source uncertainty measures affecting the reliability of experts assessments in group multi-criteria decision-making (GMCDM) problems. Abdelbasset et al. [3]modeled the imperfections of various data in smart cities and then proposed a general framework for processing imperfect and incomplete information through using SVNS and rough set theories. On the other hand, many multi-attribute decision-making(MADM) methods based on SVNS have been put forward for solving MADM problems.

In order to make a proper decision-making, Hwang and Yoon [4]originally introduced the Technique for Order Preference by Similarity to an Ideal Solution(TOPSIS) method for selecting the appropriate machine. The idea of this method is that the best alternative should have shortest distance from the positive-ideal solution and the longest distance from the negative-ideal solution. And ranking the closeness coefficient value to choose the best alternative, that is bigger coefficient value means better solution. Furthermore, Chen [5]proposed a linguistic decision-making method to solve the multiple criteria decision-making(MCDM) problem under fuzzy environment by measuring the distance between two triangular fuzzy numbers. Tsaur et al. [6] set up a process to identify the most important attributes of customer service quality and to obtain customer evaluations of the three airlines on this basis. Shih et al. [7]proposed a group TOPSIS model for decision-making without involving the work of weight elicitation in their study. The weights in their study were given by decision makers. In addition, consensus and other group interactions were not discussed interactions in their study. Opricovic and Tzeng [8]did a comparative analysis of VIKOR and TOPSIS, and the two methods use different normalizations and different aggregating functions for ranking. However, the tradeoffs involved in normalization were not considered when obtained the aggregation function. Biswas et al. [9] devoted to present a new TOPSIS-based approach for multiple attribute group decision making(MAGDM) under single-valued neutrosophic environment. Xu et al. [10] used the standard Euclidean distance and the expectation of neutrosophic number to measure the correlation between attributes, and defined a novel TODIM method to choose the best for investment. Chen et al. [11] presented an ordered weighted averaging distance applied in TOPSIS method for green supplier selection under a single-valued neutrosophic linguistic environment. Yang et al. [12]proposed a novel operational rules of Interval Neutrosophic Linguistic Sets based on Einstein operations under interval neutrosophic linguistic environment,to sort the alternatives in the MCDM problem. Garg et al. [13] presented a new method to rank the alternatives evaluated under possibility linguistic single-valued neutrosophic set domain by the TOPSIS method. Aires et al. [14] conducted an analysis to define the major cases of ranking inversion in the literature and identify the main gaps associated with the TOPSIS method. It seems that the classical TOPSIS is a good method for solving the MADM problem, but there are many emerging methods to be put forward in recent years. Pamuca and Cirovic [15] initiated a Multi-Attributive Border Approximation area Comparison (MABAC) method to solve MCDM problem. Peng and Yang [16], [17]proposed the Pythagorean fuzzy Choquet integral average operator for solving MAGDM. Xue et al. [18]proposed a MABAC

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method for material selection and used the extended group decision method to sort the alternative materials. Sun et al. [19]developed a project-based MABAC method with fuzzy language item sets and extended this method into hesitant fuzzy linguistic environment. Peng and Dai [20]proposed a new definition of single-valued neutrosophic distance measure , which can reduce information loss and keep more original information. In order to avoid the disadvantages of impractical operations. Yang et al. [21] extended the Normalized Weighted Bonferroni Mean operator to adapt to the single-valued neutrosophic environment, and analyzed some ideal properties of the new operator. Ji et al. [22]established the fuzzy outsourcing supplier selection method. The method of outsourcing supplier selection uses extended MABAC to handle single-valued neutrosophic linguistic numbers(SVNLNs). Jia et al. [23]proposed a new group information aggregation tool and extended multi-criteria group decision making(MCGDM) model based on intuitionistic fuzzy rough number. Different from the above two, a new method for solving the neutrosophic decision-making problem was proposed by Ye in 2014. He [24]defined similarity measures based on a new interval neutrosophic distance, which can be used in practical scientific and engineering applications. Meanwhile, Ye [25]proposed cross entropy measures of SVNS for decision making. Liu [26]extened Archimedean t-conorm and c-norm to SVNNs. Ye et al. [27]proposed SVNSs similarity measures based on tangent function, and developed a multi-cycle medical diagnosis method by using the similarity measure. Ye [28]introduced the concept of simplified neutrosophic set and defined the operational laws of SNS. But there was a mistake with the similarity degree.In order to conquer these shortcomings, Wang et al. [29] defined a improved similarity measure. Then, Peng and Dai [20]proposed a new axiomatic distance measure and similarity measure in the form of SVNN. Aghabozorgi et al. [30]proposed a new similarity measure between two vertices of the network, which is relying on structural units of online networks named motifs. Redrickson et al. [31]extended the similarity measure of medical event sequences using user-defined event weights.

The rest of this article is as follows: In Section 2, single-valued neutrosophic set are introduced. In Section 3, we define a new distance and a new similarity measure. In section 4, we introduce three methods to solve multi-attribute decision-making problems. In Section 5, A numerical example and a comparison analysis are shown to elaborate the proposed methods. The conclusions are drawn in section 6.

II. PRELIMINARIES OF NEUTROSOPHIC

This section gives a brief overview of concepts and definitions of neutrosophic set (NS), and single-valued neutrosophic set (SVNS).

Definition 1: [32] Let X be a space of points (objects), with a class of elements in X denoted by x. A neutrosophic set A in X is summarized by a truth-membership function $T_{A(x)}$, an indeterminacy-membership function $I_{A(x)}$, and a falsity-membership function $F_{A(x)}$.The functions $T_{A(x)}$, $I_{A(x)}$, $F_{A(x)}$ are real standard or non-standard subsets of $]0^-,1^+[$. That is $T_A(x):X\to]0^-,1^+[$ $I_A(x):X\to]\,0^-,1^+$ and $F_A(x):X\to]0^-,1^+[$. There is restriction on the sum of $T_A(x), I_A(x)$ and $F_A(x)$, so $0^- \leq \sup T_A(x)+\sup I_A(x)+\sup F_A(x)\leq 3^+$. As mentioned above, it is hard to apply the neutrosophic set to solve some real problems. Hence, Wang et al. [1]presented , which is a subclass of the neutrosophic set and mentioned the definition as follows:

Definition 2: [1] Let X be a space of points (objects), with a class of elements in X denoted by x. A single-valued neutrosophic set N in X is summarized by a truth-membership function $T_{N(x)}$, an indeterminacy-membership function $I_{N(x)}$, and a falsity-membership function $F_{N(x)}$. Then a SVNS N can be denoted as follows:

$$N=\{\langle x,T_N(x),I_N(x),F_N(x)\rangle\, x\in X\} \tag{1}$$

where $T_N(x), I_N(x), F_N(x)\in[0,1]$ for $\forall x\in X$. Meanwhile, the sum of $T_N(x), I_N(x)$, and $F_N(x)$ fulfills the condition

$$0\leq T_N(x)+I_N(x)+F_N(x)\leq 3.$$

Definition 3: [1] Let $x=(T_x,I_x,F_x)$ and $y=(T_y,I_y,F_y)$ be two SVNNs, then operations can be defined as follows:

1. $x^c=(F_x,1-I_x,T_x)$;
2. $x\oplus y=(T_x+T_y-T_x*T_y, I_x*I_y, F_x*F_y)$;
3. $x\otimes y=(T_x*T_y, I_x+I_y-I_x*I_y, F_x+F_y-F_x*F_y)$;
4. $\lambda x=\left(1-(1-T_x)^\lambda,(I_x)^\lambda,(F_x)^\lambda\right),\lambda>0$;
5. $x^\lambda=\left((T_x)^\lambda,1-(1-I_x)^\lambda,1-(1-F_x)^\lambda\right),\lambda>0.$

Definition 4: [1] For two SVNNS $x=(T_x,I_x,F_x)$ and $y=(T_y,I_y,F_y)$, if $x\leq y$ then $T_x\leq T_y, I_x\geq I_y, F_x\geq F_y$.

Definition 5: [24] Let x and y be any two SVNNs, then the Hamming distance between x and y can be defined as follows:

$$d_{Ha}(x,y)=\frac{1}{3}\left(|T_x-T_y|+|I_x-I_y|+|F_x-F_y|\right) \tag{2}$$

Definition 6: [24] Let x and y be any two SVNNs, then the Euclidean distance between x and y can be defined as follows:

$$d_E(x,y)=\sqrt{\frac{1}{3}\left((T_x-T_y)^2+(I_x-I_y)^2+(F_x-F_y)^2\right)} \tag{3}$$

Definition 7: [10] Let x and y be any two SVNNs, we can get normalized generalized distance between x and y is

$$D_g(x,y)=\frac{1}{3}\left(|T_x-T_y|^\lambda+|I_x-I_y|^\lambda+|F_x-F_y|^\lambda\right)^{\frac{1}{\lambda}} \tag{4}$$

with the condition of $\lambda>0$. When $\lambda=1$, it is the Hamming distance; when$\lambda=2$, it is the Euclidean distance.

Definition 8: [17] Let $x=(T_x,I_x,F_x)$ be a SVNN, then the proposed score function $S_{\alpha,\beta}(x)$ is defined as follows:

$$S_{\alpha,\beta}(x)=\frac{2}{3}+\frac{T_x}{3}-\alpha\frac{I_x}{3}-\beta\frac{F_x}{3} \tag{5}$$

Definition 9: Let $x=(T_x,I_x,F_x)$ be a SVNN, then the proposed accuracy function $H(x)$ is defined as follows:

$$H(x)=T_x-F_x \tag{6}$$

Definition 10: Let x, y be any two SVNNs, If $S_{\alpha,\beta}(x)<S_{\alpha,\beta}(y), x<y$, when $S_{\alpha,\beta}(x)=S_{\alpha,\beta}(y)$; If $H(x)=H(y)$ and then $x=y$, else if $H(x)<H(y)$ and then $x<y$.

III. A NEW SVNN DISTANCE AND SIMILARITY MEASURE

Definition 11: Let x and y be any two SVNNs, then the normalized single-valued neutrosophic Hausdorff distance between x and y is

$$D_{Hd} = \max\left\{\left|T_x - T_y\right|, \left|I_x - I_y\right|, \left|F_x - F_y\right|\right\} \quad (7)$$

Let x, y and z be any three SVNNs, the above defined the weighted single-value neutrosophic Hausdorff distance among x, y and z satisfies the following properties $(1)-(4)$:

(1)$D_{Hd}(x, y) \geq 0$;
(2)$D_{Hd}(x, y) = 0$ if and only if $x = y$;
(3)$D_{Hd}(x, y) = D_{Hd}(y, x)$;
(4)If $x \subseteq y \subseteq z$, then $D_{Hd}(x, z) \geq D_{Hd}(x, y)$ and $D_{Hd}(x, z) \geq D_{Hd}(y, z)$.

Proof : In order for D_{Hd} to be qualified as a reasonable distance measure for SVNSs, it must meet the $(1) - (4)$ of axiomatic requirements.

For any three SVNNs $x = (T_x, I_x, F_x)$, $y = (T_y, I_y, F_y)$ and $z = (T_z, I_z, F_z)$.

(1) $|T_x - T_y| \geq 0, |I_x - I_y| \geq 0, |F_x - F_y| \geq 0$ was established. So $\max\{|T_x - T_y|, |I_x - I_y|, |F_x - F_y|\} \geq 0$.

(2) When $D_{Hd}(x, y) = 0$. We can get that $\max\{|T_x - T_y|, |I_x - I_y|, |F_x - F_y|\} = 0$, then $|T_x - T_y| = 0, |I_x - I_y| = 0, |F_x - F_y| = 0$, that is $x = y$. On the other hand, if $x = y$, it is obvious that $D_{Hd}(x, y) = 0$.

(3) $\max\{|T_x - T_y|, |I_x - I_y|, |F_x - F_y|\} = \max\{|T_y - T_x|, |I_y - I_x|, |F_y - F_x|\}$ because of $|T_x - T_y| = |T_y - T_x|, |I_x - I_y| = |I_y - I_x|, |F_x - F_y| = |F_y - F_x|$, namely $D_{Hd}(x, y) = D_{Hd}(y, x)$.

(4) If $x \subseteq y \subseteq z$, then $T_x \leq T_y \leq T_z, I_x \geq I_y \geq I_z$ and $F_x \geq F_y \geq F_z$, hence $|T_x - T_z| \geq |T_x - T_y|$, $|I_x - I_z| \geq |I_x - I_y|$ and $|F_x - F_z| \geq |F_x - F_y|$, so $\max\{|T_x - T_z|, |I_x - I_z|, |F_x - F_z|\} \geq \max\{|T_x - T_y|, |I_x - I_y|, |F_x - F_y|\}$, Consequently $D_{Hd}(x, z) \geq D_{Hd}(x, y)$. Similarly, $D_{Hd}(x, z) \geq D_{Hd}(y, z)$. This completes the proof.

Definition 12: The normalized generalized single-valued neutrosophic Hausdorff distance between x and y is

$$D_{gHd} = \max\left\{|T_x - T_y|^{\mu}, |I_x - I_y|^{\mu}, |F_x - F_y|^{\mu}\right\}^{\frac{1}{\mu}} \quad (8)$$

$\mu > 0$, when $\mu = 1, 2, \cdots$, it is the Hausdorff distance. we get $D_{Hd} = D_{gHl}$ with any two SVNNS.

Definition 13: The weighted parameter single-valued neutrosophic distance between x and y is

$$\begin{aligned} &D_{wp}(x, y) = vD_g(x, y) + (1 - v)D_{Hd}(x, y) \\ &= \tfrac{v}{3}\left(|T_x - T_y|^{\lambda} + |I_x - I_y|^{\lambda} + |F_x - F_y|^{\lambda}\right)^{\frac{1}{\lambda}} \\ &+(1 - v)\max\left\{|T_x - T_y|, |I_x - I_y|, |F_x - F_y|\right\} \end{aligned} \quad (9)$$

where $\lambda > 0$, and $0 \leq v \leq 1$.

It is easy to prove that the definition is valid, and the proof process is omitted. If we set $\lambda = 1$, then we can get the weighted parameter from the Hamming and Hausdorff single-valued distance which is described as follows:

$$\begin{aligned} &D_{wHH}(x, y) = vD_{Ha}(x, y) + (1 - v)D_{Hd}(x, y) \\ &= \tfrac{v}{3}\left(|T_x - T_y| + |I_x - I_y| + |F_x - F_y|\right) \\ &+(1 - v)\max\left\{|T_x - T_y|, |I_x - I_y|, |F_x - F_y|\right\} \end{aligned} \quad (10)$$

Definition 14: Let x, y and z be any three SVNNs, $S(x, y)$ is a similarity measure

$$\begin{aligned} &S(x, y) = 1 - D_{wHH}(x, y) \\ &= 1 - \tfrac{v}{3}\left(|T_x - T_y| + |I_x - I_y| + |F_x - F_y|\right) \\ &-(1 - v)\max\left\{|T_x - T_y|, |I_x - I_y|, |F_x - F_y|\right\} \end{aligned} \quad (11)$$

It possesses the following properties:

(1)$0 \leq S(x, y) \leq 1$;
(2)$S(x, y) = 1$ if and only if $x = y$
(3)$S(x, y) = S(y, x)$;
(4)If $x \subseteq y \subseteq z$, then $S(x, z) \leq S(x, y)$ and $S(x, z) \leq S(y, z)$.

It can be proved that the properties are valid, and the proof process is omitted.

Based on the above fundamental knowledge, we develop three practical methods for sloving MADM problem with SVN information.

IV. THREE METHODS FOR SLOVING MADM PROBLEM

In this section, we will introduce three methods to solve MADM problems.

A. Problem description

There is a DADM problem: let $A = \{A_1, A_2, \cdots, A_m\}$ be a discrete set of alternatives, $C = \{C_1, C_2, \cdots, C_n\}$ be a series of attributes, and $W = \{W_1, W_2, \cdots, W_n\}$ be weight vector assigned for the attributes by the decision makers with $w_j \in [0, 1], \sum_{j=1}^{n} w_j = 1$. Assume that the evaluation of the alternative A_i with respect to attribute $C_j$is represented by SVN matrix.

$$R = (r_{ij})_{m\times n} = (T_{ij}, I_{ij}, F_{ij})_{m\times n} \quad (12)$$

B. Determination of weights

In this part, we obtain the attribute weights by the method in [20]. We can get the score function $S = (s_{ij})_{\text{mon}}$ $(i = 1, 2, \cdots, m; j = 1, 2, \cdots n)$ of single-valued neutrosophic matrix by eq. (5). Let $\overline{s}_i = \frac{1}{n}\sum_{j=1}^{n} s_{ij}$, then the objective weights ω_j are defined as follows:

$$\omega_j = \frac{1 - \frac{1}{m}\left(\sum_{i=1}^{m}\left(o_{ij}^{q}\right)\right)^{\frac{1}{q}}}{n - \frac{1}{m}\sum_{j=1}^{n}\left(\sum_{i=1}^{m}\left(o_{ij}^{q}\right)\right)^{\frac{1}{q}}} \quad (13)$$

Let $o_{ij} = \frac{\min_i|s_{ij} - \overline{s}_i| + \xi\max_i|s_{ij} - \overline{s}_i|}{|s_{ij} - \overline{s}_i| + \xi\max_i|s_{ij} - \overline{s}_i|}$ is gray mean relational degree, in general, we set $\xi = 0.5$. The objective weight $\omega = \{\omega, \omega_2, \cdots, \omega_n\}$, are obtained by Eq. (13) directly, where $\sum_{j=1}^{n}\omega_j = 1, 0 \leq \omega_j \leq 1$. Meanwhile the subjective weights $w = \{w_1, w_2, \cdots, w_n\}$, are given by the decision makers directly, where $\sum_{j=1}^{n} w_j = 1, 0 \leq w_j \leq 1$. Therefore, the final weights $\varpi = \{\varpi_1, \varpi_2, \cdots, \varpi_n\}$ can be defined as follows:

$$\varpi_j = \frac{w_j * \omega_j}{\sum_{j=1}^{n} w_j * \omega_j} \quad (14)$$

where $\sum_{j=1}^{n}\varpi_j = 1, 0 \leq \varpi_j \leq 1$.

C. The steps of three methods

We will briefly introduce the TOPSIS, MABAC, similarity method based on new distance measure of SVNN.

1) TOPSIS: Step 1. Identify the alternatives and attributes, and obtain the single-valued neutrosophic matrix

$R=(r_{ij})_{m\times n}=\left(T_{ij},I_{ij},F_{\tilde{j}}\right)_{m\times n}(i=1,2,\cdots,m;j=1,2,\cdots n).$

Step 2. Normalize the single-valued neutrosophic decision matrix $R=(r_{ij})_{m\times n}(i=1,2,\cdots,m;j=1,2,\cdots,n)$ into $\overline{R}=(\overline{r}_{ij})_{m\times n}=(\overline{T_{ij}},\overline{I_{ij}},\overline{F_{ij}})_{m\times n}$.

$$\overline{r_{ij}}=\begin{cases}(T_{ij},I_{ij},F_{ij}) & C_j \text{ is benefit attribute}\\ (F_{ij},1-I_{ij},T_{ij}) & C_j \text{ is cost attribute}\end{cases}$$

Step 3. Compute relative weight ϖ_j of attribute C_j by Eq. (14) .

Step 4. Determine the single-valued neutrosophic positive-ideal solution (SVN-PIS) R^+ and the single-valued neutrosophic negative-ideal solution(SVN-NIS) R^- by Eqs. (15) and (16).

$$R^+=\left\{r_1^+,r_2^+,\cdots,r_n^+\right\} \tag{15}$$

where $r_j^+=\left(T_j^+,I_j^+,F_j^+\right)(j=1,2,\cdots,n)$, and $T_j^+=\max_i\{T_{ij}\},I_j^+=\min_i\{I_{ij}\},F_j^+=\min_i\{F_{ij}\}$

$$R^-=\left\{r_1^-,r_2^-,\cdots,r_n^-\right\} \tag{16}$$

where $r_j^-=\left(T_j^-,I_j^-,F_j^-\right)(j=1,2,\cdots,n)$, and $T_j^-=\min_i\{T_{ij}\},I_j^-=\max_i\{I_{ij}\},F_j^-=\max_i\{F_i\}$. R^+ is single-valued neutrosophic positive-ideal solution (SVN-PIS) and $R^-$is single-valued neutrosophic negative-ideal solution (SVN-NIS). It can be obtained that the optimal solution should have the shortest distance from the SVN-PIS and the farthest distance from the SVN-NIS, simultaneously.

Step 5. Compute the difference of each alternative from the SVN-PIS d_i^+ and SVN-NIS $d_i^-$by Eqs. (17)and (18), respectively.

$$d_i^+=\sum_{j=1}^n w_j*D_{wHH}\left(r_{ij},R^+\right),\quad i=1,2,\cdots,m \tag{17}$$

$$d_i^-=\sum_{j=1}^n w_j*D_{wHH}\left(r_{\vec{g}},R^-\right),\quad i=1,2,\cdots,m \tag{18}$$

Step 6. Compute the closeness coefficient C_i of each alternative by Eq. (19).

$$C_i=\frac{d_i^-}{d_i^++d_i^-},i=1,2,\cdots,m \tag{19}$$

Step 7. Rank these alternatives according to the value of C_i and choose the best one with the maximum of C_i .

2) MABAC: Steps $1-3$. It is the same as the TOPSIS method.

Step 4. Compute the weighted matrix $T=(t_{ij})_{m\times n}$ by Eq .(20)

$$\begin{aligned}t_{ij}&=\left(T'_{ij},I'_{ij},F'_{ij}\right)=\varpi_j\overline{r_{ij}}\\&=\left(1-\left(1-\overline{T_{ij}}\right)^{\varpi_j},\left(\overline{I_{ij}}\right)^{\varpi_j},\left(\overline{F_{ij}}\right)^{\varpi_j}\right)\end{aligned} \tag{20}$$

Step 5. Compute the border approximation area (BAA) matrix $G=(g_j)_{1\times n}$. The BAA for each attribute is obtained by Eq. (21).

$$g_j=\prod_{i=1}^m(t_{ij})^{1/m}=$$

$$\left(\prod_{i=1}^m\left(T'_{ij}\right)^{1/m},1-\prod_{i=1}^m\left(I'_{ij}\right)^{1/m},1-\prod_{i=1}^m\left(F'_{ij}\right)^{1/m}\right) \tag{21}$$

TABLE I
THE SINGLE-VALUED NEUTROSOPHIC MATRIX $R=(r_{ij})_{5\times 3}$

	C_1	C_2	C_3
A_1	(0.0,0.0,0.0)	(1.0,0.0,0.0)	(0.0,0.0,1.0)
A_2	(0.0,0.1,0.1)	(0.9,0.1,0.2)	(0.4,0.2,0.2)
A_3	(0.1,0.1,0.1)	(0.9,0.2,0.3)	(0.5,0.3,0.2)
A_4	(0.3,0.0,0.1)	(1.0,0.1,0.2)	(0.4,0.3,0.2)
A_5	(0.0,0.1,0.0)	(0.9,0.1,0.2)	(0.4,0.3,0.2)

Step 6. Compute the distance matrix $D=(d_{ij})_{m\times n}$ by Eq. (22).

$$d_{ij}=\begin{cases}d_{wHH}(t_{ij},g_j), & \text{if } t_{ij}>g_j\\ 0, & \text{if } t_{ij}=g_j\\ -d_{\mathrm{wHH}}(t_{ij},g_j), & \text{if } t_{ij}<g_j\end{cases} \tag{22}$$

Step 7. Rank the alternatives by Q_i, where

$$Q_i=\sum_{j=1}^n d_{ij},\quad i=1,2,\cdots,m;j=1,2,\cdots,n \tag{23}$$

The most desired alternative is the one with the maximum value of Q_i .

3) similarity measure: Steps $1-3$. It is the same as the TOPSIS method.

Step 4. Calculate the ideal solution $A_j^*=\left(T_j^+,I_j^+,F_j^+\right)(j=1,2,\cdots,n)$,where $T_j^+=\max_i\{T_{ij}\},I_j^+=\min_i\{I_{ij}\},$ $F_j^+=\min_i\{F_{ij}\}$. And then compute the similarity measure $S\left(A_{ij},A_j^*\right)(i=1,2,\cdots,m,j=1,2,\cdots,n)$ by Eq. (11).

Step 5. Compute the weight similarity measure $S(A_i,A^*)$ by Eq.(24).

$$S(A_i,A^*)=\sum_{j=1}^n\varpi_j^*S\left(A_{ij},A_j^*\right)(i=1,2,\cdots,m) \tag{24}$$

Step 6. Rank the alternatives by $S(A_i,A^*)(i=1,2,\cdots,m)$. The most desired alternative is the one with the biggest value of $S(A_i,A^*)$.

V. NUMERICAL EXAMPLE

In this section, a numerical example is given to illustrate the feasibility of the three proposed methods. The decision-making problem is a municipal library selection problem with incomplete weight information. A city is going to build a municipal library. The choice of air-conditioning system in the library is one of the problem for the city development commissioner. The contractor provides five feasible alternatives $A_i(i=1,2,3,4,5)$ for library. Supposing that three attributes C_1(economic),C_2(functional) , and C_3 (operational), the subjective weight of the attribute $C_j(j=1,2,3)$ is $w=(0.5,0.2,0.3)^T$. Meanwhile,the attributes are all benefit attribute. Assume that the $A_i(i=1,2,3,4,5)$ under $C_j(j=1,2,3)$ are represented by the single-valued neutrosophic matrix $R=(r_{ij})_{5\times 3}=(T_{ij},I_{ij},F_{ij})_{5\times 3}$, see Table 1.

A. Application of TOPSIS

Step 1. The single-valued neutrosophic decision matrix $R=(r_{ij})_{5\times 3}=(T_{ij},I_{ij},F_{ij})_{5\times 3}$ which is shown in Table 1.

Step 2. Because all of the attributes are benefit attributes, so

TABLE II
THE SCORE FUNCTION MATRIX OF $S_{0.2,0.4} = (s_{ij})_{5\times3}$

	C_1	C_2	C_3
A_1	0.6667	1.0000	0.5333
A_2	0.6467	0.9333	0.7600
A_3	0.6800	0.9133	0.7867
A_4	0.7533	0.9677	0.7533
A_5	0.6600	0.9333	0.7533

TABLE III
$(o_{ij})_{5\times3}$

	C_1	C_2	C_3
A_1	1.0000	0.6333	0.3556
A_2	0.6667	0.8837	0.8889
A_3	0.7407	1.0000	1.0000
A_4	0.9677	0.9048	0.6400
A_5	0.7059	0.8906	0.8276

TABLE IV
THE d_i^+ OF DIFFERENT VALUE OF v

V	d_1^+	d_2^+	d_3^+	d_4^+	d_5^+
0.1	0.4307	0.2356	0.2274	0.1815	0.2707
0.3	0.5134	0.2949	0.2939	0.2085	0.3202
0.5	0.5526	0.3271	0.3210	0.2192	0.3430
0.7	0.5919	0.3592	0.3481	0.2298	0.3658
0.9	0.6312	0.3914	0.3752	0.2405	0.3886

TABLE V
THE d_i^- OF DIFFERENT v

V	d_1^-	d_2^-	d_3^-	d_4^-	d_5^-
0.1	0.1957	0.4052	0.3435	0.4449	0.3421
0.3	0.2332	0.3913	0.4199	0.5380	0.4263
0.5	0.2509	0.4334	0.4592	0.5843	0.4605
0.7	0.2686	0.4755	0.4985	0.6307	0.4947
0.9	0.2864	0.5176	0.5378	0.6771	0.5290

it is no need to normalize.
Step 3. compute the score function matrix $S_{0.2,0.4} = (s_{ij})_{5\times3}$, ,see Table 2. And get $\overline{S_1} = 0.73333, \overline{S_2} = 0.7800, \overline{S_3} = 0.7933, \overline{S_4} = 0.8244, \overline{S_5} = 0.7822$. Then we calculate $(o_{ij})_{5\times3}$, see Table 3. Next, the objective weights are obtained by eq.(13):

$$\omega_1 = 0.3175, \omega_2 = 0.2376, \omega_3 = 0.4449.$$

Finally, we can get the final weight by combining the objective weights and subjective weights:

$$\varpi_1 = 0.4673, \varpi_2 = 0.1399, \varpi_3 = 0.3928.$$

Step 4 Determine the SVN-PIS R^+ and SVN-NIS $R^-$by Eqs. (15) and (16), get

$$R^+ = \{\langle 0.3, 0.0, 0.0\rangle, \langle 1.0, 0.0, 0.0\rangle, \langle 0.5, 0.0, 0.2\rangle\}$$
$$R^- = \{\langle 0.0, 0.1, 0.1\rangle, \langle 0.9, 0.2, 0.3\rangle, \langle 0.0, 0.3, 1.0\rangle\}$$

Step 5 Compute the difference of each alternative from the SVN-PIS d_i^+ shows in Table 4 and SVN-NIS d_i^- shows in Table 5 by Eqs. (17) and (18), the results are shown as follows:

Step 6. Calculate the closeness coefficient C_i of each alternative by Eq. (19), see Table 6.

TABLE VI
THE C_i^+ OF DIFFERENT VALUE OF v

V	C_1	C_2	C_3	C_4	C_5
0.1	0.3125	0.6323	0.6017	0.7103	0.5582
0.3	0.3123	0.5702	0.5883	0.7207	0.5711
0.5	0.3122	0.5699	0.5885	0.7272	0.5731
0.7	0.3122	0.5696	0.5888	0.7329	0.5749
0.9	0.3121	0.5694	0.5890	0.7379	0.5765

TABLE VII
RANKING ORDER AND THE FINAL CHOICE

v	Ranking Order	FC
0.1	$A_4 > A_2 > A_3 > A_5 > A_1$	A_4
0.3	$A_4 > A_3 > A_5 > A_2 > A_1$	A_4
0.5	$A_4 > A_3 > A_5 > A_2 > A_1$	A_4
0.7	$A_4 > A_3 > A_5 > A_2 > A_1$	A_4
0.9	$A_4 > A_3 > A_5 > A_2 > A_1$	A_4

TABLE VIII
THE WEIGHED SVN MATRIX $T = (t_{ij})_{5\times3}$

	C_1	C_2	C_3
A_1	(0.0000,0.0000,0.0000)	(1.0000,0.0000,0.0000)	(0.0000,0.0000,1.0000)
A_2	(0.0000,0.7246,0.4048)	(0.6590,0.7246,0.5314)	(0.2124,0.7984,0.5314)
A_3	(0.0480,0.7246,0.4048)	(0.6590,0.7984,0.6231)	(0.2767,0.8450,0.5314)
A_4	(0.1535,0.0000,0.4048)	(1.0000,0.7246,0.5314)	(0.2124,0.8450,0.5314)
A_5	(0.0000,0.7246,0.0000)	(0.6590,0.7246,0.5314)	(0.2124,0.8450,0.5314)

TABLE IX
THE SVN MATRIX $D = (d_{ij})_{5\times3}$ BY $v = 0.1$,

	C_1	C_2	C_3
A_1	0.5117	0.6441	0.7119
A_2	-0.1781	-0.1154	0.4456
A_3	-0.1797	-0.1440	0.4493
A_4	0.5125	0.2104	0.4472
A_5	0.2559	-0.1154	0.4472

Step 7. The final ranking: FC denotes the final choice which is shown in Table 7. Clearly, the best alternative is A_4. We can find the different ranking order with different value of v. And with the increasing of v, the gap between alternatives can be bigger and bigger. If the difference of alternatives are not obvious, it can be easy to choose the best choice when we increase the value of v. Meanwhile, it shows that the final choice is fixed.

B. Application of MABAC

Step $1 - 3$. It is the same as the TOPSIS section.

Step 4. Calculate the weighted matrix $T = (t_{ij})_{5\times3}$ by Eq. (20), which is shown in Table 8.

Step 5. The BAA $G = (g_j)_{1\times3}$ is determined according to the Eq. (21), we can get

$$g_1 = (0.0000, 0.5387, 0.2675)$$
$$g_2 = (0.7786, 0.6651, 0.4479)$$
$$g_3 = (0.0000, 0.7628, 1.0000).$$

Step 6. Calculate the distance matrix $D = (d_{ij})_{5\times3}$ by Eq. (22) with different value of v, when $v = 0.1, D = (d_{ij})_{5\times3}$ is shown in Table 9.

when $v = 0.3, D = (d_{ij})_{5\times3}$ is shown in Table 10.

when $v = 0.5, D = (d_{ij})_{5\times3}$ is shown in Table 11.

TABLE X
THE SVN MATRIX $D = (d_{ij})_{5\times 3}$ BY $v = 0.3$,

	C_1	C_2	C_3
A_1	0.6190	0.8749	0.7628
A_2	-0.2271	-0.1535	0.5230
A_3	-0.2415	-0.2211	0.5762
A_4	0.6259	0.2553	0.5569
A_5	0.3232	-0.1535	0.5569

TABLE XI
THE SVN MATRIX $D = (d_{ij})_{5\times 3}$ BY $v = 0.5$,

	C_1	C_2	C_3
A_1	0.6725	1.0148	0.7628
A_2	-0.2545	-0.1761	0.5925
A_3	-0.2786	-0.2717	0.6480
A_4	0.6841	0.2779	0.6158
A_5	0.3605	-0.1761	0.6158

TABLE XII
THE SVN MATRIX $D = (d_{ij})_{5\times 3}$ BY $v = 0.7$,

	C_1	C_2	C_3
A_1	0.7260	1.1546	0.7628
A_2	-0.2820	-0.1987	0.6421
A_3	-0.3156	-0.3223	0.7198
A_4	0.7422	0.3005	0.6748
A_5	0.3976	-0.1987	0.6748

TABLE XIII
THE SVN MATRIX $D = (d_{ij})_{5\times 3}$ BY $v = 0.9$,

	C_1	C_2	C_3
A_1	0.7795	1.2944	0.7628
A_2	-0.3094	-0.2213	0.6917
A_3	-0.3527	-0.3728	0.7916
A_4	0.8004	0.3231	0.7337
A_5	0.4348	-0.2213	0.7337

TABLE XIV
THE VALUE OF Q_i

v	Q_1	Q_2	Q_3	Q_4	Q_5
0.1	1.8677	0.1522	0.1256	0.8184	0.5877
0.3	1.6700	0.1303	0.1020	0.7439	0.5300
0.5	1.4722	0.1083	0.0784	0.6693	0.4722
0.7	1.2744	0.0864	0.0548	0.5948	0.4145
0.9	1.0769	0.0645	0.0312	0.5203	0.3568

when $v = 0.7, D = (d_{ij})_{5\times 3}$ is shown in Table 12.
when $v = 0.9, D = (d_{ij})_{5\times 3}$ is shown in Table 13.

Step 7. Compute the value of $Q_i(i = 1, 2, \cdots, m)$, which is shown in Table 14. Then rank the alternatives by $Q_i(i = 1, 2, \cdots, m)$ and obtain the final choice, which is shown in Table 15.

The best alternative is A_1, which is different from TOPSIS method. We can also find that the ranking order and final choice are not changed with different value of v .

C. Application of similarity measure

Step $1 - 3$. It is the same as the TOPSIS section.

TABLE XV
THE RANKING ORDER AND FC

v	Ranking Order	FC
0.1	$A_1 > A_4 > A_5 > A_2 > A_3$	A_1
0.3	$A_1 > A_4 > A_5 > A_2 > A_3$	A_1
0.5	$A_1 > A_4 > A_5 > A_2 > A_3$	A_1
0.7	$A_1 > A_4 > A_5 > A_2 > A_3$	A_1
0.9	$A_1 > A_4 > A_5 > A_2 > A_3$	A_1

TABLE XVI
THE WEIGHT SIMILARITY MEASURE $S^{\Delta}(A_i, A^*)\,(i = 1, 2, \cdots, m)$

v	$S(A_1, A^*)$	$S(A_2, A^*)$	$S(A_3, A^*)$	$S(A_4, A^*)$	$S(A_5, A^*)$
0.1	0.5721	0.7647	0.7623	0.8232	0.7340
0.3	0.6168	0.7865	0.7838	0.8406	0.7598
0.5	0.6643	0.8087	0.8086	0.8628	0.7903
0.7	0.7118	0.8309	0.8333	0.8849	0.8209
0.9	0.7593	0.8531	0.8581	0.9070	0.8514

TABLE XVII
THE RANKING ORDER AND FC

v	Ranking Order	FC
0.1	$A_4 > A_2 > A_3 > A_5 > A_1$	A_4
0.3	$A_4 > A_2 > A_3 > A_5 > A_1$	A_4
0.5	$A_4 > A_2 > A_3 > A_5 > A_1$	A_4
0.7	$A_4 > A_3 > A_2 > A_5 > A_1$	A_4
0.9	$A_4 > A_3 > A_2 > A_5 > A_1$	A_4

Step 4. It is easy to get $A_1^* = (0.0, 0.0, 0.0), A_2^* = (1.0, 0.1, 0.0), A_3^* = (0.5, 0.0, 0.2)$. When $v = 0.1$ we can get that

$$S(A_{11}, A_1^*) = 0.72, S(A_{12}, A_2^*) = 1.00, S(A_{13}, A_3^*) = 0.24,$$
$$S(A_{21}, A_1^*) = 0.71, S(A_{22}, A_2^*) = 0.81, S(A_{23}, A_3^*) = 0.81,$$
$$S(A_{31}, A_1^*) = 0.81, S(A_{32}, A_2^*) = 0.71, S(A_{33}, A_3^*) = 0.72,$$
$$S(A_{41}, A_1^*) = 0.91, S(A_{42}, A_2^*) = 0.81, S(A_{43}, A_3^*) = 0.72,$$
$$S(A_{51}, A_1^*) = 0.72, S(A_{52}, A_2^*) = 0.81, S(A_{53}, A_3^*) = 0.72.$$

We can use the same way to calculate the similarity measure when $v = 0.3, 0.5, 0.7, 0.9$.

Step 5. Calculate the weight similarity measure $S^{\Delta}(A_i, A^*)\,(i = 1, 2, \cdots, m)$ by Eq.(24), which is shown in Table16.

Step 6. Rank the alternatives by $S^{\Delta}(A_i, A^*)\,(i = 1, 2, \cdots, m)$, which is shown in Table 17.

So the best choice is A_4. We can find that the ranking order is variational with different value of v, but the final choice is fixed, which is the same with TOPSIS method.

D. A comparison analysis

In order to better verify the practicability of the multi-attribute decision making methods based on TOPSIS, MABAC and similarity measure of SVNNs and compared with the existing methods.The decision data adopts [33]. If the existing methods in Ye [24], [25], Biswas et al. [9], Liu [26], Li et al. [34], Peng et al. [20], and the proposed three methods are utilized to solve the MADM problem in this example, then the results can be obtained and shown in Table 18. From the results shown in Table 17, we can easy to find some interesting things. We can get various answers when we use different methods to solve the same question. Meanwhile, even the same author can get different

TABLE XVIII
A COMPARISON ANALYSIS

Method	The Ranking Order	FC
Ye [24]	$A_4 > A_2 > A_5 > A_1 > A_3$	A_4
Ye [25]	$A_4 > A_3 > A_5 > A_1 > A_2$	A_4
Biswas et al. [9]	$A_4 > A_3 > A_2 > A_5 > A_1$	A_4
Liu [26]	$A_1 > A_4 > A_5 > A_3 > A_2$	A_1
Li et al. [34]	$A_4 > A_3 > A_5 > A_1 > A_2$	A_4
Peng et al. [20]	$A_4 > A_3 > A_5 > A_2 > A_1$	A_4
Peng et al. [20]	$A_4 > A_1 > A_5 > A_2 > A_3$	A_4
Method 1(v=0.1)	$A_4 > A_2 > A_3 > A_5 > A_1$	A_4
Method 1(v=0.1)	$A_4 > A_3 > A_5 > A_2 > A_1$	A_4
Method 2	$A_1 > A_4 > A_5 > A_2 > A_3$	A_1
Method 1(v=0.1)	$A_4 > A_2 > A_3 > A_5 > A_1$	A_4
Method 1(v=0.9)	$A_4 > A_3 > A_2 > A_5 > A_1$	A_4

results. From the results we can find that different parameter maybe get various final ranking, but we can get the same optimal alternative. All of the methods get the same optimal alternative except method 2 and Liu [26]. Coincidentally, their results were very similar to each other.

VI. CONCLUSION

We consider a new distance in SVNNs distance, which includes weight parameter. Firstly we define some basic knowledge of the SVN, which is involving TOPSIS, MABAC, and similarity measure. Secondly, we introduce these three methods, which can efficaciously solve decision-making problems with the inconsistent information. Then we give a numerical example and use these three methods to solve this question and get the final choice from these three methods. We can find that the ranking order maybe have a little change, but the final choice is fixed. It shows that when we change the value of v, which means changing the weight of the two distances in the combined distance, we can get the same result. We can further deduce whether all the distance formulas will get the same result when calculating the distance, so when we encounter the distance calculation in the future, we can use the simplest distance calculation method to calculate the distance between the two SVNNs. This hypothesis deserves further examination. Finally, we do a comparison analysis with others who solved this example before. We can inspection the hypothesis by more parameters for combined distance and use this distance to solve other questions in the interval neutrosophic sets in the future.

REFERENCES

[1] Z. Y. Wang H, Smarandache F and S. Ro, “Single valued neutrosophic sets,” *Multispace Multistruc*, vol. 4, pp. 410–413, 2010.

[2] M. A. Sodenkamp, M. Tavana, and D. D. Caprio, “An aggregation method for solving group multi-criteria decision-making problems with single-valued neutrosophic sets,” *Applied Soft Computing*, vol. 71, pp. 715–727, 2018.

[3] M. Abdelbasset and M. Mohamed, “The role of single valued neutrosophic sets and rough sets in smart city: Imperfect and incomplete information systems,” *Measurement*, vol. 124, pp. 47–55, 2018.

[4] Hwang and Yoon, “Multiple attributes decision making methods and applications,” *Springer*, vol. 404, pp. 139–262, 1981.

[5] C. Chen, “Extensions of the topsis for group decision-making under fuzzy environment,” *Fuzzy Sets and Systems*, vol. 114, no. 1, pp. 1–9, 2000.

[6] S. Tsaur, T. Chang, and C. Yen, “The evaluation of airline service quality by fuzzy mcdm,” *Tourism Management*, vol. 23, no. 2, pp. 107–115, 2002.

[7] H. Shih, H. Shyur, and E. S. Lee, “An extension of topsis for group decision making,” *Mathematical and Computer Modelling*, vol. 45, no. 7, pp. 801–813, 2007.

[8] S. Opricovic and G. Tzeng, “Compromise solution by mcdm methods: A comparative analysis of vikor and topsis,” *European Journal of Operational Research*, vol. 156, no. 2, pp. 445–455, 2004.

[9] P. Biswas, S. Pramanik, and B. C. Giri, “Topsis method for multi-attribute group decision-making under single-valued neutrosophic environment,” *Neural Computing and Applications*, vol. 27, no. 3, pp. 727–737, 2016.

[10] X. Dongsheng, H. Yanran, and Q. Han, “Multiple attribute decision making based on neutrosophic sets in venture capital,” *Engineering Letters*, vol. 26, no. 4, pp. 441–446, 2018.

[11] J. Chen, S. Zeng, and C. Zhang, “An owa distance-based, single-valued neutrosophic linguistic topsis approach for green supplier evaluation and selection in low-carbon supply chains,” *International Journal of Environmental Research and Public Health*, vol. 15, no. 7, p. 1439, 2018.

[12] L. Yang and B. Li, “Novel power aggregation operators based on einstein operations for interval neutrosophic linguistic sets,” *IAENG International Journal of Applied Mathematics*, vol. 48, no. 4, pp. 108–117, 2018.

[13] H. Garg and Nancy, “Algorithms for possibility linguistic single-valued neutrosophic decision-making based on copras and aggregation operators with new information measures,” *Measurement*, vol. 138, pp. 278–290, 2019.

[14] R. F. D. F. Aires and L. V. Ferreira, “A new approach to avoid rank reversal cases in the topsis method,” *Computers and Industrial Engineering*, vol. 132, pp. 84–97, 2019.

[15] D. Pamucar and G. Cirovic, “The selection of transport and handling resources in logistics centers using multi-attributive border approximation area comparison (mabac),” *Expert Systems With Applications*, vol. 42, no. 6, pp. 3016–3028, 2015.

[16] X. Peng and Y. Yang, “Some results for pythagorean fuzzy sets,” *Journal of intelligent systems*, vol. 30, no. 11, pp. 1133–1160, 2015.

[17] ——, “Pythagorean fuzzy choquet integral based mabac method for multiple attribute group decision making,” *Journal of intelligent systems*, vol. 31, no. 10, pp. 989–1020, 2016.

[18] Y. Xue, J. You, X. Lai, and H. Liu, “An interval-valued intuitionistic fuzzy mabac approach for material selection with incomplete weight information,” *Applied Soft Computing*, vol. 38, pp. 703–713, 2016.

[19] R. Sun, J. Hu, J. Zhou, and X. Chen, “A hesitant fuzzy linguistic projection-based mabac method for patients prioritization,” *International Journal of Fuzzy Systems*, vol. 20, no. 7, pp. 2144–2160, 2018.

[20] X. Peng and J. Dai, “Approaches to single-valued neutrosophic madm based on mabac, topsis and new similarity measure with score function,” *Neural Computing and Applications*, vol. 29, no. 10, pp. 939–954, 2018.

[21] Y. Lihua and L. Baolin, “An extended single-valued neutrosophic normalized weighted bonferroni mean einstein aggregation operator,” *IAENG International Journal of Applied Mathematics*, vol. 48, no. 4, pp. 373–380, 2018.

[22] P. Ji, H. Zhang, and J. Wang, “Selecting an outsourcing provider based on the combined mabaccelectre method using single-valued neutrosophic linguistic sets,” *Computers and Industrial Engineering*, vol. 120, pp. 429–441, 2018.

[23] F. Jia, Y. Liu, and X. Wang, “An extended mabac method for multi-criteria group decision making based on intuitionistic fuzzy rough numbers,” *Expert Systems With Applications*, vol. 127, pp. 241–255, 2019.

[24] J. Ye, “Multiple attribute group decision-making method with completely unknown weights based on similarity measures under single valued neutrosophic environment,” *Journal of Intelligent and Fuzzy Systems*, vol. 27, no. 6, pp. 2927–2935, 2014.

[25] ——, “Improved cross entropy measures of single valued neutrosophic sets and interval neutrosophic sets and their multicriteria decision making methods,” *Cybernetics and Information Technologies*, vol. 15, no. 4, pp. 13–26, 2015.

[26] P. Liu, “The aggregation operators based on archimedean t-conorm and t-norm for single-valued neutrosophic numbers and their application to decision making,” *International Journal of Fuzzy Systems*, vol. 18, no. 5, pp. 849–863, 2016.

[27] J. Ye and J. Fu, “Multi-period medical diagnosis method using a single valued neutrosophic similarity measure based on tangent function,” *Computer Methods and Programs in Biomedicine*, vol. 123, pp. 142–149, 2016.

[28] J. Ye, “Single-valued neutrosophic similarity measures based on cotangent function and their application in the fault diagnosis of steam turbine,” *soft computing*, vol. 21, no. 3, pp. 817–825, 2017.

[29] J. Peng, J. Wang, J. Wang, H. Zhang, and X. Chen, “Simplified neutrosophic sets and their applications in multi-criteria group decision-

making problems," *International Journal of Systems Science*, vol. 47, no. 10, pp. 2342–2358, 2016.

[30] F. Aghabozorgi and M. R. Khayyambashi, "A new similarity measure for link prediction based on local structures in social networks," *Physica A-statistical Mechanics and Its Applications*, vol. 501, pp. 12–23, 2018.

[31] J. Fredrickson, M. V. Mannino, O. Alqahtani, and F. Banaeikashani, "Using similarity measures for medical event sequences to predict mortality in trauma patients," *decision support systems*, vol. 116, pp. 35–47, 2019.

[32] F. Smarandache, "A unifying field in logics: Neutrosophic logic, neutrosophic set, neutrosophic probability and statistics (fourth edition)," *arXiv: General Mathematics*, 2001.

[33] Z. Xu and R. R. Yager, "Intuitionistic fuzzy bonferroni means," *systems man and cybernetics*, vol. 41, no. 2, pp. 568–578, 2011.

[34] Y. Li, P. Liu, and Y. Chen, "Some single valued neutrosophic number heronian mean operators and their application in multiple attribute group decision making," *Informatica (lithuanian Academy of Sciences)*, vol. 27, no. 1, pp. 85–110, 2016.

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