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Research Article

Multiple Attribute Group Decision Making Based on Simplified Neutrosophic Integrated Weighted Distance Measure and Entropy Method

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Simplified neutrosophic set (SNS) is a popular tool in modelling potential, imprecise, and uncertain information within complex environments. In this paper, a method based on the integrated weighted distance measure and entropy weight is proposed for handling SNS multiple attribute group decision-making (MAGDM) problems. To this end, the simplified neutrosophic (SN) integrated weighted distance (SVNIWD) measure is first developed for overcoming the limitations of the existing methods. Afterward, the proposed SNIWD's several properties and particular status are studied. Moreover, a flexible and useful MAGDM approach that combines the strengths of the SNIWD and the SNS is proposed, wherein the SN entropy measure is applied to calculate the unknown weight information regarding attributes. Finally, a numerical case of investment evaluation and subsequent comparative analysis are conducted to prove the superiority of the proposed framework.

1. Introduction

The aim of the multiple attribute group decision-making (MAGDM) problem is to determine suitable alternatives with respect to multiple attributes according to the judgement provided by various decision makers. It is impossible for a decision maker to always express an accurate preference because of the increasing uncertainties of the assessed problems. To solve the difficulties, many effective mathematical tools are introduced during the decision process. The fuzzy set (FS) firstly developed by Zadeh [1] is widely used to model imprecise and vague information in MAGDM. An element's membership value in fuzzy theory lies in the range [0, 1], while the value of its complement is called the nonmembership. To provide a more effective method, the conception of intuitionistic FS (IFS) was proposed by Atanassov [2] which is described by membership and nonmembership functions, and their sum cannot exceed 1. Later, Yager [3] presented the Pythagorean FS (PFS), whose special merit is that the square sum of the membership and nonmembership shall lie in interval [01,]. Thus, the PFS is a more powerful tool to describe uncertainties than the IFS and FS. Up to now, the PFS has gained more and more attention and has been widely used in decision making as well as other areas [4–15].

Recently, Smarandache [16] defined the idea of the neutrosophic set (NS) utilizing three parameters: the degrees of truth, indeterminacy, and false for the first time. These three components in the NS are entirely irrelevant from each other, which help people present their preference more flexibly and accurately compared with the previous IFS and PFS. To enhance the computational efficiency of the NS, Wang et al. [17] and Ye [18] put forward the concept of simplified neutrosophic set (SNS). The SNS has gained increasing attention from researchers in these years because of its preponderance in describing uncertainties. For example, Ye [19] extended the TOPSIS method to handle simplified neutrosophic (SN) environments and studied its application in selecting suppliers. Peng et al. [20] introduced an outranking method for SN MAGDM problems. Peng et al. [21]

developed some aggregation methods for SN information. Kucuk and Sahin [22] provided a hybrid method for SN decision-making in which the weight information is unknown. Ye [23] gave a netting approach to cluster SN information based on new associated coefficients. Sahin and Liu [24] developed several SN aggregation operators utilizing the possibility information. Liu and Luo [25] proposed a power aggregation to infuse the SNS and explored its usefulness in MAGDM. Ye [26] introduced a generalized ordered weighted SN cosine similarity measure and applied it to solve MAGDM problems. Zeng et al. [27] presented a novel TOPSIS approach for SN decision-making considering the high-efficiency correlation coefficient. Peng and Dai [28] conducted a bibliometric survey of the development concerning the neutrosophic set from 1998 to 2017.

Various distance measures have been put forward and used in decision-making process for reflecting the deviations between the arguments. One of the most widely used distances is the weighted distance, including weighted Hamming and weighted Euclidean distances [29]. Motivated by the ideal of the ordered weighted method [30], Xu and Chen [31] presented the ordered weighted distance (OWD) measure considering the importance of the ordered deviations by designing weight scheme. Later, Merigó and Gil-Lafuente [32] presented the ordered weighted averaging distance (OWAD) measure, and applied it to evaluate financial products. So far, a variety extensions of the OWD and the OWAD measures have been presented in the literature. Xu and Xia [33] explored the OWD with hesitant fuzzy information and developed the hesitant fuzzy OWD and hybrid weighted similarity measures. Zeng and Su [34] adapted the OWD into the IFS situation and presented the intuitionistic fuzzy OWD (IFOWD). Zeng [37] studied the usefulness of the IFOWD using a generalized mean method. Shakeel et al. [38] developed the cubic OWD (COWD) and gave its application in decision-making. Zhou et al. [37, 38] worked on several continuous OWD measures. Some authors also extended the OWD and the OWAD using more complex variables, such as the logarithmic means [39, 40], induced aggregation [41–43], and weighted average [44–46]. More recently, considering the usefulness of the SNS, Sahin and Kucuk [47] proposed the simplified neutrosophic OWD (SNOWD) and studied its performance in the group decision-making problem.

With awareness the capabilities of the SNS which are analyzed above, the purpose of this research is to propose a new SN distance measure that can correct the shortcomings of the existing methods and apply it to MAGDM. To this end, we present the simplified neutrosophic integrated weighted distance (SNIWD) measure, which combines the significance of the existing SNOWD and SN weighted distance (SNWD) measures. Therefore, it can eliminate the limitations of the SNOWD that cannot account for the importance of attribute in MAGDM problems. Moreover, it generalizes a wide kind of existing SN distance measures, including the SNOWD and the SNWD measures. We also verify the merits of the proposed SNIWD measure by exploring its application to MAGDM problems, in which the weight information of attributes is unknown.

The reminder of this paper is carried out as follows: Section 2 gives the backgrounds of the SNS and the OWD measure. Section 3 defines the SNIWD measure and studies its main properties and various cases. Section 4 constructs a MAGDM model based on the SNIWD measure and entropy measure, and a mathematical example is provided in Section 5. Finally, Section 6 draws some valuable conclusions.

2. Preliminaries

2.1. The Simplified Neutrosophic Set (SNS)

Definition 1 (see [16]). A neutrosophic set (NS) P in a finite set X is denoted as

$$P = \left\{ \langle x, T_P(x), I_P(x), F_P(x) \rangle \mid x \in X \right\}, \tag{1}$$

where $T_P(x)$,$I_P(x)$, and $F_P(x)$ are called the truth, the indeterminacy, and the falsity-membership functions, respectively. Moreover, $T_P(x)$, $I_P(x)$ and $F_P(x)$ are the standard and nonstandard subsets of real numbers $]0^-, 1^+[$ and satisfy

$$0^- \leq \sup T_P(x) + \sup I_P(x) + \sup F_P(x) \leq 3^+. \tag{2}$$

To extend the application of the NS in engineering and science areas, Ye [18] defined the simplified neutrosophic set (SNS).

Definition 2 (see [18]). A simplified neutrosophic set (SNS) Q in a finite set X is described in the following form:

$$Q = \left\{ \langle x, T_Q(x), I_Q(x), F_Q(x) \rangle \mid x \in X \right\}, \tag{3}$$

where $T_\eta(x)$, $I_\eta(x)$, and $F_\eta(x)$ represent the truth, the indeterminacy, and the falsity-membership functions, respectively, and satisfy

$$\begin{aligned} &0 \leq T_Q(x), I_Q(x), F_Q(x) \leq 1, \\ &0 \leq T_Q(x) + I_Q(x) + F_Q(x) \leq 3. \end{aligned} \tag{4}$$

For convenience, element $q = (T_q, I_q, F_q)$ is generally named as a simplified neutrosophic number (SNN), and the complement of $q = (T_q, I_q, F_q)$ is defined as $q^c = (F_q, 1 - I_q, T_q)$.

Let $q = (T_q, I_q, F_q)$ and $s = (T_s, I_s, F_s)$ be two SNNs; some of mathematical operations are provided by Ye [18]:

(1) $q \oplus s = (T_q + T_s - T_q * T_s, I_q * T_s, F_q * F_s)$
(2) $\lambda q = (1 - (1 - T_q)^\lambda, (I_q)^\lambda, (F_q)^\lambda)$ $(\lambda > 0)$

Definition 3 (see [19]). Let$x_i = (T_{x_i}, I_{x_i}, F_{x_i})$ $(i = 1, 2)$ be two SNNs; then, the Hamming distance measure between x_1 and x_2 is presented as follows:

$$d_{\mathrm{SNN}}(x_1, x_2) = \frac{1}{3}\left(\left|T_{x_1} - T_{x_2}\right| + \left|I_{x_1} - I_{x_2}\right| + \left|F_{x_1} - F_{x_2}\right| \right). \tag{5}$$

On the basis of the distance measure defined in equation (5), Sahin and Kucuk [47] proposed a SN similar measure between x_1 and x_2 as follows:

$$\mathrm{SM}_{\mathrm{SNN}}(x_1, x_2) = \frac{d_{\mathrm{SNN}}(x_1, x_2^c)}{d_{\mathrm{SNN}}(x_1, x_2) + d_{\mathrm{SNN}}(x_1, x_2^c)}. \quad (6)$$

2.2. The SNOWD Measure

Definition 4 (see [47]). Let $Q = \{q_1, q_2, \ldots, q_n\}$ and $S = \{s_1, s_2, \ldots, s_n\}$ be two collections of SNNs, and $d_{\mathrm{SNN}}(q_i, s_i)$ is the distance between SNNs q_i and s_i; then, the simplified neutrosophic weighted distance (SNWD) measure can be defined as follows:

$$\mathrm{SNWD}(Q, S) = \left(\sum_{i=1}^{n} \omega_i \left(d_{\mathrm{SNN}}(q_i, s_i) \right)^k \right)^{1/k}, \quad (7)$$

where $k > 0$ and $\omega = (\omega_1, \omega_2, \ldots, \omega_n)$ is the weighted vector of $d_{\mathrm{SNN}}(q_i, s_i)$ such that $\omega_i \in [0, 1]$and$\sum_{i=1}^{n} \omega_i = 1$.

Motivated by the OWD measure [31], Sahin and Kucuk [47] proposed the conception of the SNOWD measure, whose significance property is the ordered mechanism for the aggregated information.

Definition 5 (see [47]). Let $Q = \{q_1, q_2, \ldots, q_n\}$and $S = \{s_1, s_2, \ldots, s_n\}$ be two sets of SNNs, and $d_{\mathrm{SNN}}(q_i, s_i)$ is the distance between SNNs q_i and s_i; then, the simplified neutrosophic ordered weighted distance (SNOWD) measure is defined as

$$\mathrm{SNOWD}(Q, S) = \left(\sum_{i=1}^{n} w_i \left(d_{\mathrm{SNN}}\left(q_{\sigma(i)}, s_{\sigma(i)}\right) \right)^k \right)^{1/k}, \quad (8)$$

where $d_{\mathrm{SNN}}(q_{\sigma(i)}, s_{\sigma(i)})\,(i = 1, 2, \ldots, n)$ is the reorder values such that $d_{\mathrm{SNN}}(q_{\sigma(1)}, s_{\sigma(1)}) \geq d_{\mathrm{SNN}}(q_{\sigma(2)}, s_{\sigma(2)}) \geq \cdots \geq d_{\mathrm{SNN}}(q_{\sigma(n)}, s_{\sigma(n)})$. The associated weight vector of the SNOWD is $w = (w_1, w_2, \ldots, w_n)$ with $\sum_{i=1}^{n} w_i = 1$ and $w_i \in [0, 1]$.

The SNOWD measure possesses some good properties that the OWD also has, including boundedness, commutativity, idempotency, and monotonicity. However, the SNOWD can only consider the weights of ordered deviations, but fail to reflect the weights (importance) of aggregated arguments that the SNWD can. Therefore, we shall propose an integrated weighted distance measure to eliminate the existing defects in the SNOWD measure.

3. SN Integrated Weighted Distance (SNIWD) Measure

It is observed from Definitions 1 and 5 that the SNWD can reflect the importance of the input argument but fails to account for the positions' weights of the ordered distances that the SNOWD can, while the SNOWD cannot emphasize the importance of aggregated deviations that the SNWD can. To solve the limitations, we present the SN integrated weighted distance (SNIWD) measure that can combine both merits of the SNOWD and the SNWD measures.

Definition 6. Let $Q = \{q_1, q_2, \ldots, q_n\}$ and $S = \{s_1, s_2, \ldots, s_n\}$ be two collections of SNNs, and $d_{\mathrm{SNN}}(q_i, s_i)$ is the distance between SNNs q_i and s_i; then, the SNIWD measure is defined as

$$\mathrm{SNIWD}(Q, S) = \left(\sum_{i=1}^{n} \psi_i \left(d_{\mathrm{SNN}}\left(q_{\sigma(i)}, s_{\sigma(i)}\right) \right)^k \right)^{1/k}, \quad (9)$$

where the integrated weights ψ_i are defined as

$$\psi_i = \varepsilon w_i + (1 - \varepsilon)\omega_{\sigma(i)}, \quad (10)$$

wherein ω_i is the weight of $d_{\mathrm{SNN}}(q_i, s_i)$ $(i = 1, 2, \ldots, n)$ such that $\omega_i \in [0, 1]$ and $\sum_{i=1}^{n} \omega_i = 1$, w_i is the relative weight of the SNIWD satisfying $\sum_{i=1}^{n} w_i = 1$ and$w_i \in [0, 1]$, and ε is a real parameter satisfying $\varepsilon \in [0, 1]$.

Obviously, when $\varepsilon = 1$and $\varepsilon = 0$, the SNIWD is generalized to the SNOWD and the SNWD measures, respectively. Therefore, the SNIWD can be viewed as a combination of the SNOWD and SNWD measures, which can be proved by the following formula:

$$\mathrm{SNIWD}(Q, S) = \left(\sum_{i=1}^{n} \psi_i \left(d_{\mathrm{SNN}}\left(q_{\sigma(i)}, s_{\sigma(i)}\right) \right)^k \right)^{1/k} = \left(\varepsilon \sum_{i=1}^{n} w_i \left(d_{\mathrm{SNN}}\left(q_{\sigma(i)}, s_{\sigma(i)}\right) \right)^k + (1 - \varepsilon) \sum_{i=1}^{n} \omega_i \left(d_{\mathrm{SNN}}(q_i, s_i) \right)^k \right)^{1/k}. \quad (11)$$

Example 1. Let

$$\begin{aligned} Q &= \{(0.9, 0.4, 0.7), (0.6, 0.2, 0.4), (0.4, 0.8, 0.5), (0.7, 0.1, 0.6)\}, \\ S &= \{(0.5, 0.5, 0.3), (0.5, 0.4, 0.1), (0.3, 0.7, 0.4), (0.4, 0.4, 0.1)\}, \end{aligned} \quad (12)$$

be two collections of SNNs; then, the computational procedure of the SNIWD is listed as follows:

(1) Utilize equation (5) to calculate $d_{\mathrm{SNN}}(q_i, s_i)$ $(i = 1, 2, \ldots, 4)$:

$$\begin{aligned} d_{\mathrm{SNN}}(q_1, s_1) &= 0.3, \\ d_{\mathrm{SNN}}(q_2, s_2) &= 0.2, \\ d_{\mathrm{SNN}}(q_3, s_3) &= 0.1, \\ d_{\mathrm{SNN}}(q_4, s_4) &= 0.4. \end{aligned} \quad (13)$$

(2) Rank $d_{\mathrm{SNN}}(q_i, s_i)$ $(i = 1, 2, \ldots, 4)$ according to the decreasing order:

$$\begin{aligned} d_{\mathrm{SNN}}\left(q_{\sigma(1)}, s_{(1)}\right) &= d_{\mathrm{SNN}}\left(q_4, s_4\right) = 0.4, \\ d_{\mathrm{SNN}}\left(q_{\sigma(2)}, s_{(2)}\right) &= d_{\mathrm{SNN}}\left(q_1, s_1\right) = 0.3, \\ d_{\mathrm{SNN}}\left(q_{\sigma(3)}, s_{(3)}\right) &= d_{\mathrm{SNN}}\left(q_2, s_2\right) = 0.2, \\ d_{\mathrm{SNN}}\left(q_{\sigma(3)}, s_{(4)}\right) &= d_{\mathrm{SNN}}\left(q_3, s_3\right) = 0.1. \end{aligned} \tag{14}$$

(3) Let $w = (0.22, 0.28, 0.36, 0.14)$ and $\omega = (0.2, 0.4, 0.1, 0.3)$; then, compute the integrated weights ψ_i according to equation (10) (let $\varepsilon = 0.6$):

$$\begin{aligned} \psi_1 &= 0.6 \times 0.22 + (1 - 0.6) \times 0.3 = 0.252, \\ \psi_2 &= 0.6 \times 0.28 + (1 - 0.6) \times 0.2 = 0.248, \\ \psi_3 &= 0.6 \times 0.36 + (1 - 0.6) \times 0.4 = 0.376, \\ \widehat{w}_4 &= 0.6 \times 0.14 + (1 - 0.6) \times 0.1 = 0.124. \end{aligned} \tag{15}$$

(4) Let $k = 2$; then, calculate the distance between Qand Sutilizing the SNIWD measure defined in equation (9):

$$\begin{aligned} \mathrm{SNIWD}(Q, S) &= \left(\sum_{i=1}^{4} \psi_i \left(d_{\mathrm{SNN}}\left(q_{\sigma(i)}, s_{\sigma(i)}\right)\right)^2 \right)^{1/2} \\ &= \left(0.252 \times 0.4^2 + 0.248 \times 0.3^2 + 0.376 \times 0.2^2 + 0.124 \times 0.1^2\right)^{1/2} \\ &= 0.2809. \end{aligned} \tag{16}$$

We can also illustrate the aggregation by applying the SNIWD measure given in equation (11):

$$\begin{aligned} \mathrm{SNIWD}(Q, S) &= \left(\sum_{i=1}^{4} \psi_i \left(d_{\mathrm{SNN}}\left(q_{\sigma(i)}, s_{\sigma(i)}\right)\right)^2 \right)^{1/2} \\ &= \left(0.6 \times \left(\sum_{i=1}^{n} w_i \left(d_{\mathrm{SNN}}\left(q_{\sigma(i)}, s_{\sigma(i)}\right)\right)^2 \right) + (1 - 0.6) \times \left(\sum_{i=1}^{n} \omega_i \left(d_{\mathrm{SNN}}\left(q_i, s_i\right)\right)^2 \right) \right)^{1/2} \\ &= (0.6 \times 0.0762 + (1 - 0.6) \times 0.083)^{1/2} \\ &= 0.2809. \end{aligned} \tag{17}$$

Obviously, the same results are rendered by both methods. Following the aforementioned definitions and the example, we can see that the SNIWD possesses the dual aggregated functions by combining the ordered weighted and arithmetic weighed methods, i.e., it covers both features of the previous SNOWD and the SNWD measures as it weights both the deviations and their ordered positions. Thus, it can not only reflect the weights of the input arguments themselves but also highlight the importance of their ordered positions during aggregation process. Moreover, it provides a possibility for decision makers to select suitable parameters according to actual demands or interests.

The SNIWD measure generalizes a wide range of SN distance measures by designing different values of the weights and parameters, for example:

Remark 1. Let $k = 1$; then, we obtain the SN integrated weighted Hamming distance (SNIWHD) measure, and the SN integrated weighted Euclidean distance (SNIWED) measure is formed when $k = 2$.

Remark 2. If $\varepsilon = 1$, then the SNIWD is reduced to the SNOWD measure. Thus, all particular SN distance measures of the SNOWD mentioned in the result of Sahin and Kucuk [47] are the SNIWD's special cases, for example:

(i) The SN Hamming ordered weighted distance (SNHOWD) measure ($k = 1$)
(ii) The SN Euclidean ordered weighted distance (SNEOWD) measure ($k = 2$)
(iii) The SN geometric ordered weighted distance (SNGOWD) measure ($k \longrightarrow 0$)
(iv) Maximum SN distance measure ($w = (1, 0, 0, \ldots, 0)$)
(v) Minimum SN distance measure ($w = (0, 0, \ldots 0, 1)$)
(vi) Normalized SN distance measure ($w = (1/n, 1/n, \ldots, 1/n)$)

Remark 3. If $\varepsilon = 0$, then the SNIWD is reduced to the SNWD measure. Then, we can achieve various families of the

SNWD that can be seen as the SNIWD's particular status, such as:

(i) The SN Hamming weighted distance (SNHWD) measure ($k = 1$)

(ii) The SN Euclidean weighted distance (SNEWD) measure ($k = 2$)

(iii) The SN geometric weighted distance (SNGWD) measure ($k \longrightarrow 0$)

(iv) Normalized SN distance measure ($\omega = (1/n, t1/nn, q \ldots h,_{1/n)})$)

Remark 4. By applying similar analysis introduced in the recent literature [48–53], more other cases of the SNIWD measure can be created, such as the the centered-SNIWD, median-SNIWD, and the Olympic-SNIWD measures.

The following theorems show that the SNIWD measure satisfies some desirable properties of monotonicity, boundedness, idempotency, commutativity, and reflexivity.

Theorem 1 (monotonicity). If $d_{\mathrm{SNN}}(q_i, s_i) \geq d_{\mathrm{SNN}}(q_i', s_i')$ for $i = 1, 2, \ldots, n$, then

$$\mathrm{SNIWD}((q_1, s_1), \ldots, (q_n, s_n)) \geq \mathrm{SNIWD}((q_1', s_1'), \ldots, (q_n', s_n')). \tag{18}$$

Theorem 2 (idempotency). If $d_{\mathrm{SNN}}(q_i, s_i) = d$ for $i = 1, 2, \ldots, n$, then

$$\mathrm{SNIWD}((q_1, s_1), \ldots, (q_n, s_n)) = d. \tag{19}$$

Theorem 3 (boundedness). Let $d_{\min} = \min_i (d_{\mathrm{SNN}}(q_i, s_i))$ and $d_{\max} = \max_i (d_{\mathrm{SNN}}(q_i, s_i))$; then,

$$d_{\min} \leq \mathrm{SNIWD}((q_1, s_1), \ldots, (q_n, s_n)) \leq d_{\max}. \tag{20}$$

Theorem 4 (commutativity). If $((q_1', s_1'), \ldots, (q_n', s_n'))$ is any permutation of $((q_1, s_1), \ldots, (q_n, s_n))$, then

$$\mathrm{SNIWD}((q_1, s_1), \ldots, (q_n, s_n)) = \mathrm{SNIWD}((q_1', s_1'), \ldots, (q_n', s_n')). \tag{21}$$

Theorem 5 (reflexivity). If $q_i = s_i$ for $i = 1, 2, \ldots, n$, then

$$\mathrm{SNIWD}((q_1, s_1), \ldots, (q_n, s_n)) = 0. \tag{22}$$

4. Application in MAGDM

As a generalization of various distance measures, the SNIWD is applicable to many fields, such as data analysis, decision-making, social management, pattern recognition, and financial investment. In this section, an application in the MAGDM problems is studied. Suppose that a MAGDM problem has $m$different alternatives $B_1, B_2, \ldots, B_m$, and some experts $E_1, E_2, \ldots, E_t$ are consulted to assess n finite attributes $C_1, C_2, \ldots, C_n$. Following the available information, the general procedure based on the SNIWD and entropy measures for MAGDM can be summarized as follows.

Step 1. Construct the SN individual decision matrix $R^l = (r_{ij}^{(l)})_{m\times n}$, where $r_{ij}^{(l)} = (T_{ij}^{(l)}, I_{ij}^{(l)}, F_{ij}^{(l)})$ provided by expert e_l $(l = 1, 2, \ldots, t)$ is a SNN denoting the assessment of alternative B_i with respect to attribute C_j.

Step 2. Determine the weight vector of experts (or decision makers) based on the similarity measure method [47]. In some actual problems, the weights of the experts cannot be determined beforehand. Thus, we introduce a method to derive the weights' information of experts based on the similar measures between individual opinions $R^l = (r_{ij}^{(l)})_{m\times n}$ and the overall decision matrix $R^* = (r_{ij}^{(*)})_{m\times n}$:

$$\mathrm{sm}\left(R^{(l)}, R^*\right) = \sum_{i=1}^{n} \sum_{j=1}^{m} \mathrm{sm}\left(r_{ij}^{(l)}, r_{ij}^*\right), \tag{23}$$

where the distance measure $\mathrm{sm}(r_{ij}^{(l)}, r_{ij}^*)$ between $r_{ij}^{(l)}$ and r_{ij}^* can be calculated by equation (6) and $r_{ij}^{(*)} = (T_{ij}^{(*)}, I_{ij}^{(*)}, F_{ij}^{(*)})$ is the mean value of $r_{ij}^{(l)} = (T_{ij}^{(l)}, I_{ij}^{(l)}, F_{ij}^{(l)})$ $(l = 1, 2, \ldots, t)$ determined by the following formula:

$$T_{ij}^{(*)} = \frac{1}{t} \sum_{l=1}^{t} T_{ij}^{(l)}, I_{ij}^{(*)} = \frac{1}{t} \sum_{l=1}^{t} I_{ij}^{(l)}, F_{ij}^{(*)} = \frac{1}{t} \sum_{l=1}^{t} F_{ij}^{(l)}. \tag{24}$$

On the basis of the similar measures, the weight of expert e_l $(l = 1, 2, \ldots, t)$ can be derived by the following equation:

$$\theta_l = \frac{\mathrm{sm}\left(R^{(l)}, R^{(*)}\right)}{\sum_{l=1}^{t} \mathrm{sm}\left(R^{(l)}, R^{(*)}\right)}, \tag{25}$$

where $\theta_i \in [0, 1]$, and $\sum_{i=1}^{t} \theta_i = 1$. Moreover, the weight of experts derived by this method has the desirable characteristic: the larger the similarity $\mathrm{sm}(R^{(l)}, R^*)$ is, the more closer the individual evaluation $R^{(l)}$ to the overall evaluation $R^*$is and the larger the weight of expert e_l $(l = 1, 2, \ldots, t)$ is.

Step 3. Calculate the collective decision matrix $R = (\,^{ij}_{r})_{m\times n}$using the SN weighted averaging (SNWA) operator [21], where $r_{ij} = (T_{ij}, I_{ij}, F_{ij}) = \sum_{l=1}^{t} \theta_l r_{ij}^{(l)}$.

Step 4. Determine the weight vector of the attribute. It is often difficult to express the weight information of the attribute in advance due to time limited or experts' professional knowledge. Thus, we develop an entropy-based method to derive the importance of attribute C_j $(j = 1, 2, \ldots, n)$:

$$\omega_j = \frac{1 - E_j}{n - \sum_{j=1}^{n} E_j}. \tag{26}$$

$\omega_i \in [0, 1]$ and $\sum_{i=1}^{n} \omega_i = 1$, and the entropy measure E_j introduced by Biswas et al. [54] can be calculated from the following equationfd16:

$$E_j = \frac{1}{m} \sum_{i=1}^{m} \left(1 - \left|2I_{ij} - 1\right| \times \left(T_{ij} + F_{ij}\right)\right). \tag{27}$$

Step 5. Set ideal scheme $I = (I_1, I_2, \ldots, I_n)$ utilizing the following formula:

$$I_j = \left(T_{I_j}, I_{I_j}, F_{I_j}\right) = \begin{cases} \left(\max_i T_{ij}, \min_i I_{ij}, \min_i Fi_j\right), & \text{for the benefit attribute,} \\ \left(\min_i T_{ij}, \max_i I_{ij}, \max_i F_{ij}\right), & \text{for the cost attribute.} \end{cases} \quad (28)$$

Step 6. Apply the SNIWD measure to calculate the distances between alternative $B_i\,(i = 1, 2, \ldots, m)$ and ideal scheme I:

$$\mathrm{SWIND}\left(B_i, I\right) = \left(\sum_{j=1}^{m} \psi_j d_{\mathrm{SNN}}\left(r_{\sigma(ij)}, I_{\sigma(j)}\right)^k\right)^{1/k}, \quad i = 1, 2, \ldots, n. \quad (29)$$

Step 7. Rank the alternatives in accordance with the results obtained in the previous step, and hence, select the best choice.

5. Numerical Case of Investment Selection

In this section, we give a mathematical example of the investment selection problem [21] to verify the effectiveness and applicability of the presented method. A company would like to invest a sum of money to get a good return. Four possible alternatives are considered: (1) B_1 is a computer company; (2) B_2 is a food company; (3) B_3 is a car company; and (4) B_4 is an arms company. Three experts $\{E_1, E_2, E_3\}$ are invited to assess the companies from the following attributes: C_1 is the risk analysis; C_2 is the environmental impact analysis, and $C_3$is the growth analysis, wherein C_1 and $C_3$are of the benefit types, while C_2 belongs to the cost type. Then, the decision procedures are illustrated as follows.

Step 1. The individual SN decision matrix provided by experts is listed in Tables 1–3.

Step 2. On the basis of the aforementioned decision matrix, the overall decision matrix $R^* = (r_{ij}^{(*)})_{m\times n}$ is calculated by using equation (24), listed in Table 4.

Using equation (25), the similar measures between individual opinions $R^{(l)}\,(l = 1, 2, 3)$ and the overall decision matrix $R^*$are calculated as

$$\begin{aligned} \mathrm{sm}\left(R^{(1)}, R^*\right) &= 0.883, \\ \mathrm{sm}\left(R^{(2)}, R^*\right) &= 0.903, \\ \mathrm{sm}\left(R^{(3)}, R^*\right) &= 0.896. \end{aligned} \quad (30)$$

Thus, the weights of experts are derived as

$$\begin{aligned} \theta_1 &= 0.329, \\ \theta_2 &= 0.337, \\ \theta_3 &= 0.334. \end{aligned} \quad (31)$$

Step 3. According to the weights of the experts, the collective SN decision matrix can be calculated by using the SNWA operator, presented in Table 5.

Step 4. Applying equations (26) and (27), the weight vector of attributes is computed as $\omega = (0.3634, 0.2862, 0.3504)$.

Step 5. The results of the ideal scheme by applying equation (28) are calculated as given in Table 6.

Step 6. Without loss of generality, let the parameter and wight vector of the SNIWD measure be $\varepsilon = 0.5$and $w = (0.3, 0.5, 0.2)$, respectively. Then, based on the weights of attributes obtained in Step 5, the distances between each alternative $B_i\,(i = 1, 2, 3, 4)$ and ideal scheme$I$ are calculated by using equation (29):

$$\begin{aligned} \mathrm{SNIWD}\left(B_1, I\right) &= 0.1526, \\ \mathrm{SNIWD}\left(B_2, I\right) &= 0.0922, \\ \mathrm{SNIWD}\left(B_3, I\right) &= 0.1070, \\ \mathrm{SNIWD}\left(B_4, I\right) &= 0.0945. \end{aligned} \quad (32)$$

Step 7. Rank all the alternatives in accordance with the decreasing values of $\mathrm{SNIWD}(B_i, I)$. The smaller the value of $\mathrm{SNIWD}(B_i, I)$, the closest B_i to the ideal scheme, and thus the better alternative B_i. Therefore, the alternatives can be ranked as

$$B_2 \succ B_4 \succ B_3 \succ B_1. \quad (33)$$

Hence, the best alternative is B_2.

Moreover, we can apply some special cases of the SNWID mentioned in Section 4 to calculate the relative distances from the alternatives to the ideal scheme for obtaining a more comprehensive picture. The aggregation results are shown in Table 7, and the subsequent ranking order is listed in Table 8.

It can be seen in Table 8 that different ranking lists can be achieved from different cases of the SNIWD measures. Therefore, this method presents a more flexible mechanism for decision makers to choose different schemes according to their own needs or actual situations.

To perform the applicability of the presented method, we conduct a comparative research on some existing approaches for handling SN decision-making problems. We select the correlation coefficient method proposed by Ye [55], cross-entropy method by Ye [56], TOSIS method developed by Zeng et al., [27], SNWA method introduced by

Table 1: SN decision matrix $R^{(1)}$.

	C_1	C_2	C_3
B_1	(0.6, 0.2, 0.3)	(0.5, 0.1, 0.2)	(0.5, 0.1, 0.3)
B_2	(0.5, 0.3, 0.2)	(0.5, 0.3, 0.3)	(0.7, 0.1, 0.3)
B_3	(0.5, 0.1, 0.2)	(0.3, 0.1, 0.3)	(0.5, 0.2, 0.2)
B_4	(0.5, 0.3, 0.2)	(0.7, 0.2, 0.2)	(0.7, 0.2, 0.2)

Table 2: SN decision matrix $R^{(2)}$.

	C_1	C_2	C_3
B_1	(0.4, 0.1, 0.3)	(0.6, 0.2, 0.2)	(0.5, 0.3, 0.3)
B_2	(0.6, 0.1, 0.2)	(0.5, 0.2, 0.3)	(0.7, 0.2, 0.3)
B_3	(0.5, 0.2, 0.2)	(0.3, 0.2, 0.4)	(0.6, 0.2, 0.3)
B_4	(0.7, 0.3, 0.1)	(0.5, 0.1, 0.2)	(0.6, 0.3, 0.2)

Table 3: SN decision matrix $R^{(3)}$.

	C_1	C_2	C_3
B_1	(0.3, 0.2, 0.3)	(0.5, 0.3, 0.2)	(0.5, 0.2, 0.3)
B_2	(0.6, 0.1, 0.2)	(0.5, 0.2, 0.2)	(0.6, 0.1, 0.2)
B_3	(0.4, 0.2, 0.3)	(0.2, 0.2, 0.5)	(0.4, 0.2, 0.3)
B_4	(0.7, 0, 0.1)	(0.4, 0.3, 0.2)	(0.6, 0.1, 0.2)

Table 4: Overall decision matrix R^*.

	C_1	C_2	C_3
B_1	(0.448, 0.159, 0.262)	(0.552, 0.182, 0.200)	(0.500, 0.182, 0.300)
B_2	(0.569, 0.144, 0.200)	(0.500, 0.229, 0.262)	(0.670, 0.126, 0.262)
B_3	(0.469, 0.159, 0.229)	(0.268, 0.159, 0.391)	(0.507, 0.200, 0.262)
B_4	(0.644, 0.000, 0.126)	(0.552, 0.182, 0.200)	(0.637, 0.182, 0.200)

Table 5: Collective SN decision matrix R.

	C_1	C_2	C_3
B_1	(0.447, 0.158, 0.263)	(0.536, 0.182, 0.200)	(0.500, 0.182, 0.300)
B_2	(0.570, 0.144, 0.200)	(0.500, 0.229, 0.262)	(0.670, 0.126, 0.262)
B_3	(0.469, 0.159, 0.229)	(0.268, 0.159, 0.392)	(0.507, 0.200, 0.263)
B_4	(0.645, 0.000, 0.126)	(0.551, 0.190, 0.200)	(0.636, 0.182, 0.200)

Table 6: Ideal scheme.

	C_1	C_2	C_3
I	(0.645, 0.000, 0.126)	(0.268, 0.229, 0.392)	(0.670, 0.126, 0.200)

Peng et al. [21], ordered weighted SN cosine similarity measure [26], and power aggregation model provided by Liu and Luo [25]. All the ranking lists are illustrated in Table 9.

It is noted from Table 9 that the best choice is either B_2 or B_4, and the ranking lists of all alternatives may vary depending on the decision method used. The main reasons can be summarized as follows:

(1) The proposed SNIWD and the entropy model can efficiently eliminate the large deviation opinions provided by experts through the ordered weighting mechanism, which widely exists in MAGDM problems.

(2) An entropy model is put forward to derive the unknown weights' information of attributes in this paper. By contrast, the weights of attributes are determined by decision makers (experts) in advance in the aforementioned methods.

Table 7: Aggregated results rendered by particular cases of the SNIWD.

	Maximum	Minimum	SNWHD	SNWED	SNOWHD	SNOWED	SNIWHD
B_1	0.1643	0.1087	0.1462	0.1487	0.1546	0.1563	0.1504
B_2	0.1207	0.0207	0.0773	0.0883	0.0892	0.0961	0.0833
B_3	0.146	0.0233	0.0948	0.1068	0.0985	0.1073	0.0966
B_4	0.1713	0.0000	0.0595	0.0933	0.0633	0.0962	0.0630

Table 8: Ranking results obtained by particular cases of the SNIWD.

Method	Ranking
Maximum	$B_2 \succ B_3 \succ B_1 \succ B_4$
Minimum	$B_4 \succ B_1 \succ B_2 \succ B_3$
SNWHD	$B_2 \succ B_4 \succ B_3 \succ B_1$
SNWED	$B_2 \succ B_4 \succ B_3 \succ B_1$
SNOWHD	$B_4 \succ B_2 \succ B_3 \succ B_1$
SNOWED	$B_2 \succ B_4 \succ B_3 \succ B_1$
SNIWHD	$B_4 \succ B_2 \succ B_3 \succ B_1$

Table 9: Ranking results obtained by the existing decision-making method.

Method	Ranking
Correlation coefficient method [55]	$B_4 \succ B_1 \succ B_2 \succ B_3$
Cross-entropy method [56]	$B_4 \succ B_2 \succ B_3 \succ B_1$
TOSIS method [27]	$B_2 \succ B_4 \succ B_1 \succ B_3$
SNWA method [21]	$B_2 \succ B_4 \succ B_3 \succ B_1$
Ordered weighted cosine similarity measure method [26]	$B_2 \succ B_4 \succ B_3 \succ B_1$
Power aggregation method [25]	$B_4 \succ B_2 \succ B_3 \succ B_1$

6. Conclusions

In this study, we present a new approach based on the integrated distance measure and entropy weights for MAGDM with SN information. The SNIWD measure is proposed to improve the defects of the previous methods. The main advantage of the SNIWD is that it combines the ordered weighted and arithmetic weighted functions for reflecting the SN deviations. Moreover, it generalizes a great many of SN distance measures, including the SNOWD and the SNWD. Then, we develop a MAGDM approach based on the SNIWD and the entropy method within SN situations, wherein the entropy measure is utilized to determine the unknown weight information. A case study regarding selection of a suitable investment case is given to illustrate the efficiency of the proposed framework. The results and comparative study with other existing models test the advantages and effectiveness of our method. The preponderances of the proposed method based on the SNIWD measure and the entropy weight are summed up as follows: (1) the existing approaches based on the ordered weighted distance measures in decision-making areas only pay attention to the weights of the ordered deviation. They fail to account for the importance of attributes. By contrast, the introduced method based on the SNIWD can effectively fuse both importance of the ordered deviations and attributes; (2) the attribute weight is given by decision makers in advance in the existing literature. However, we present an entropy measure method to derive the unknown attribute weight information, which helps to achieve a more objective result; and (3) the proposed method based on the SNIWD is more flexible as it provides a chance for the decision maker to select the appropriate parameters that are near to his or her interests or the needs of the decision-making problems.

In our subsequent study, we will consider some other applications of the proposed approach, such as education evaluation and social network. Some new extensions by using other variables are also considered in complex situations.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare no conflicts of interest.

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