Hindawi
Mathematical Problems in Engineering
Volume 2020, Article ID 7279420, 11 pages
https://doi.org/10.1155/2020/7279420

Research Article

The Projection Model with Unknown Weight Information under Interval Neutrosophic Environment and Its Application to Software Quality-in-Use Evaluation

Tongjuan Wang

Department of Software Engineering, Shandong Polytechnic College, Jining 272067, China

Correspondence should be addressed to Tongjuan Wang; 2219185045@qq.com

Received 28 October 2019; Revised 30 December 2019; Accepted 28 January 2020; Published 24 February 2020

Academic Editor: Weifeng Pan

Interval neutrosophic sets (INSs) provide us with a more flexible and effective way to express incomplete, indeterminate, and inconsistent information. The purpose of this paper is to introduce the new multicriteria decision-making (MCDM) method based on the improved projection model under the interval neutrosophic environment. In this paper, we investigated the basic concepts and operational rules of interval neutrosophic numbers (INNs), then proposed the projection of two INNs and improved the entropy formula of the INNs. Furthermore, this paper took account into the decision maker's attitude towards the indeterminacy and risk and proposed two different methods to determine the ideal solutions. Based on this, we presented an improved MCDM method based on the projection model under the interval neutrosophic environment. Finally, the practicability and reliability of the proposed method were explained by the example of software quality-in-use evaluation.

1. Introduction

Zadeh [1] proposed the concept of fuzzy set (FS), which could effectively deal with the fuzzy information, and has been effectively applied to the fields of fuzzy decision-making, fuzzy control, pattern recognition, and so on. Based on the idea of FSs, Atanassov added nonmembership function and introduced the concept of intuitionistic fuzzy set (IFS) [2]. Then, Atanassov and Gargov [3] introduced the concept of interval-valued intuitionistic fuzzy set (IVIFS), which uses the form of interval numbers to represent the membership and nonmembership. This form provides a more flexible way to express fuzzy and uncertain information. However, IFS and IVIFS still have some shortcomings in representing indeterminacy information. To overcome these shortcomings, Smarandache [4] proposed the concept of neutrosophic set (NS), which takes three parameters into account including truth-membership, indeterminacy-membership, and falsity-membership. This form deals with not only the incomplete information but also the indeterminate information and inconsistent information clearly and effectively. Its advantage is to quantify the uncertainty clearly. Different from those of IFS and IVIFS, the truth information, the indeterminacy information, and the falsity information of NS are irrelevant. Considering that, the neutrosophic set put forward the concept of indeterminacy-membership on the basis of IFS. And it is the generalization of FS, IFS, and IVIFS. Therefore, it is difficult to apply the neutrosophic set to the practical decision-making environment. Wang et al. extended the neutrosophic set and proposed the concepts of both single-valued neutrosophic set (SVNS) [5] and interval neutrosophic set (INS) [6]. In contrast with NS, SVNS, and INS, practical problems can be solved more easily and effectively. In view of the flexibility and practicability of INS in dealing with uncertain information, it has attracted extensive attention in the field of multicriteria decision-making (MCDM). An INS is an instance of an NS, and it would be more suitable to apply the indeterminate information and inconsistent information measures [7]. In view that INS represents truth-membership, indeterminacy-membership, and falsity-membership in the form of the interval number, the expression of INS is prone to be more inclusive and flexible when dealing with uncertain information. Therefore, the INS will provide an effective method to solve the uncertainty in the real environment.

Yu et al. [8–10] conducted a bibliometric analysis of related periodicals, such as fuzzy optimization and decision-making, which is valuable for the further study of MCDM. The recent research is divided into two trends. One is the innovation and development of fuzzy sets, such as NS [11, 12], SVNS, INS, and other concepts. The other is to combine new concepts with more mature MCDM methods and further innovate and apply these methods. Among them, the research on the single value neutrosophic set mainly includes basic concepts, operational rules, similarity measurement, distance measurement, entropy measurement, definition of cross entropy [13, 14], aggregation operator [15–18], and decision method [19, 20]. INS adopts the form of the interval number to represent the truth information, indeterminacy information, and falsity information, which can effectively catch and express more information in case of uncertainty [21]. Ridvan [22] and Tian et al. [23] provided the definition of the interval neutrosophic crossentropy and proposed several multicriteria decision-making methods based on this. Ye [24] utilized the similarity measures with interval neutrosophic sets between each alternative and the ideal alternative to rank the alternatives and meanwhile determine the better one. Bolturk and Kahraman [25] developed a novel AHP method with cosine similarity measure under the INS environment. Sun et al. [26] proposed a choquet integral operator with interval neutrosophic numbers for MCDM. Zhang et al. [27, 28] developed the MCDM methods with simplified neutrosophic number (SNNs) and interval neutrosophic numbers (INNs). In addition, Liu et al. [29–31] also studied the MCDM method under the interval neutrosophic environment and made some progress. Pramanik et al. proposed the definitions of in-crossentropy and similarity measure and introduced an extended grey relational analysis method under the interval neutrosophic environment [32–34]. The properties and applications of multivalued neutrosophic set, neutrosophic cubic set [35–39], picture fuzzy set [40, 41], and linguistic neutrosophic set [42–45] will be considered as the direction of some scholars in the next stage of research studies. In addition, Ashraf also studied the properties, operational rules, and aggregation operators of spherical fuzzy sets and linguistic spherical fuzzy sets, then further studied their application to multiattribute decision-making problems [46–54]. Spherical fuzzy sets will also become a research direction in fuzzy decision-making. These studies will inject new vitality into the uncertain decision-making.

The neutrosophic set regards the truth, falsity, and indeterminacy information as mutually independent. Taking the single-valued neutrosophic number as an example, it can be seen that changes in one value do not directly affect changes in other values. The range of its three parameters is [0, 1]. We determined the comprehensive information by synthesizing the values of three parameters. As shown in Figure 1(b), point K is the geometric representation of a single-valued neutrosophic number. Relatively, for an

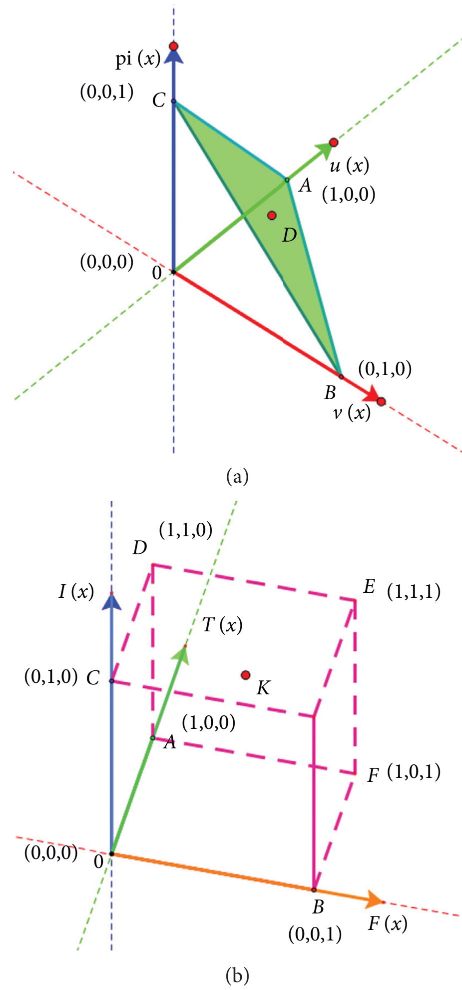

Figure 1: Geometric representation of (a) intuitionistic fuzzy number and (b) single-valued neutrosophic number.

intuitionistic fuzzy set $A = \{\langle x, \mu_A(x), \nu_A(x)\rangle \mid x \in X\}$, it is not hard for us to find that $\mu_A(x) + \nu_A(x) + \pi_A(x) = 1$; therefore, the changes of values of $\mu_A(x)$ and $\nu_A(x)$ directly affect the value of $\pi_A(x)$. In Figure 1(a), point D is the geometric representation of an intuitionistic fuzzy number and the abovementioned three parameters are linearly correlated. Therefore, it is not suitable to copy the formula of ranking, entropy, crossentropy, and the distance of two intuitionistic fuzzy numbers to the SVNS and INS. Given the abovementioned reasons, combining with the characteristics of the neutrosophic set, the problem of how to treat the indeterminacy information becomes the key to the ranking method of neutrosophic numbers, the calculation of the expected value, and the distance between two neutrosophic numbers. Most studies tend to accept the conclusion as follows that, for two SVNNs or INNs, if the values of their truth membership and falsity-membership are identical, the larger the indeterminacy value is, the smaller the SVNN will be, which is based on the fact that people are inclined to choose the alternative with lower uncertainty. However, that is not always the case. If we try to adopt the prospect theory to interpret single-valued neutrosophic set, we may find that the previous conclusion is not constant. According to the certainty effect of prospect theory, given two single neutrosophic numbers $x = [0.5, 0.7, 0.1]$ and $y = [0.5, 0.4, 0.1]$, and meanwhile $0.5 - 0.1 = 0.4$, the truth information dominates for the two numbers. The advantages are obvious. We tend to choose the number with the lower value of indeterminacy information. Based on the abovementioned description, we can draw the following conclusion, that is, $x > y$. On the contrary, given two neutrosophic numbers $x = [0.1, 0.7, 0.5]$ and $y = [0.15, 0.1, 0.5]$, according to the reflection effect of prospect theory, because $0.1 - 0.5 = -0.4$, the falsity information dominates for two numbers. The psychology of decision makers is often that since the result is terrible, a gamble may bring the good result. As a consequence, they are apt to choose the number with the higher indeterminacy value. When we compare two numbers, generally speaking, it is easy to make a comparison provided that one has more obvious advantages over the other. By employing different methods, we can obtain the same result. But often, there are some numbers with high similarity, which make it difficult to make a comparison. Different comparison methods may result in different results, for instance, the comparison of two numbers $x = [0.1, 0.1, 0.5]$ and $y = [0.15, 0.15, 0.55]$. Despite that scholars have put forward many comparative methods, it is still hard to determine which one is appropriate. This is a matter of consideration. The difficulty of conducting the research is to figure out the compensation mode between different parameters. From the abovementioned examples, we come to a conclusion that the attitude of decision makers towards indeterminacy information will be the foundation of the comparison of two neutrosophic numbers. Similarly, the attitude of decision makers towards indeterminacy information also affects the determination of positive and negative ideal schemes.

The rest of paper was organized as follows. In Section 2, this paper introduced some related concepts of INSs and operational rules of INNs and meanwhile provided the new ranking method for INNs. In Section 3, this paper gave the definition for the projection of two INNs and improved the entropy weight formula. Section 4 proposed an MCDM method based on the projection model and improved entropy weight. In Section 5, this paper illustrated the steps of the proposed method for evaluating the quality-in-use of software. Finally, the further research work was introduced in Section 6.

2. Preliminaries

2.1. Neutrosophic Sets and Single-Valued Neutrosophic Sets

2.1.1. Interval Neutrosophic Sets. An interval neutrosophic set (INS) is an instance of NS, which can be used in real decision and graphic image processing. The definitions of interval neutrosophic set and numbers are given as follows.

Definition 1 [see 6]. Let U be a space of points (objects) and $\mathrm{Int}[0,1]$ be the set of all closed subsets of $[0,1]$. An interval neutrosophic set B in U is defined with the form

$$B = \left\{ [x, (T_B(x), I_B(x), F_B(x))] \mid x \in U \right\}, \tag{1}$$

where the intervals $T_B(x) = [T^L(x), T^U(x)] \subseteq [0,1]$, $I_B(x) = [I^L(x), I^U(x)] \subseteq [0,1]$, and $F_B(x) = [F^L(x), F^U(x)] \subseteq [0,1]$ denote truth-membership function, indeterminacy-membership function, and falsity -membership function, respectively:

$$0 \le \sup T_A(x) + \sup I_A(x) + \sup F_A(x) \le 3. \tag{2}$$

So, we can use $x = ([T^L, T^U], [I^L, I^U], [F^L, F^U])$ to represent the elements of the interval neutrosophic set, that is, the interval neutrosophic number (see Figure 2).

Definition 2 (see [24]). Let $x = ([T_1^L, T_1^U], [I_1^L, I_1^U], [F_1^L, F_1^U])$ and $y = ([T_2^L, T_2^U], [I_2^L, I_2^U], [F_2^L, F_2^U])$ be two interval neutrosophic numbers, and then the Hamming distance can be defined as follows:

$$d(x,y) = \frac{1}{6}\Big(\left|T_1^L - T_2^L\right| + \left|T_1^U - T_2^U\right| + \left|I_1^L - I_2^L\right| + \left|I_1^U - I_2^U\right| + \left|F_1^L - F_2^L\right| + \left|F_1^U - F_2^U\right| \Big). \tag{3}$$

Definition 3 (see [11]). Let $x = ([T_1^L, T_1^U], [I_1^L, I_1^U], [F_1^L, F_1^U])$ and $y = ([T_2^L, T_2^U], [I_2^L, I_2^U], [F_2^L, F_2^U])$ be two interval neutrosophic numbers, and then the operational rules of interval neutrosophic numbers can be defined as follows:

$$\overline{x} = \left(\left[F_1^L, F_1^U\right], \left[1 - I_1^U, 1 - I_1^L\right], \left[T_1^L, T_1^U\right] \right), \tag{4}$$

$$x \oplus y = \left(\left[T_1^L + T_2^L - T_1^L T_2^L, T_1^U + T_2^U - T_1^U T_2^U\right], \left[I_1^L I_2^L, I_1^U I_2^U\right], \left[F_1^L F_2^L, F_1^U F_2^U\right] \right), \tag{5}$$

$$x \otimes y = \begin{pmatrix} \left[T_1^L T_2^L, T_1^U T_2^U\right] \\ \left[I_1^L + I_2^L - I_1^L I_2^L, I_1^U + I_2^U - I_1^U I_2^U\right] \\ \left[F_1^L + F_2^L - F_1^L F_2^L, F_1^U + F_2^U - F_1^U F_2^U\right] \end{pmatrix}, \tag{6}$$

$$\lambda x = \left(\left[1 - \left(1 - T_1^L\right)^\lambda, 1 - \left(1 - T_1^U\right)^\lambda\right], \left[\left(I_1^L\right)^\lambda, \left(I_1^U\right)^\lambda\right], \left[\left(F_1^L\right)^\lambda, \left(F_1^U\right)^\lambda\right] \right), \lambda > 0, \tag{7}$$

$$x^\lambda = \begin{pmatrix} \left[(T_1^L)^\lambda, (T_1^U)^\lambda\right] \\ \left[1 - (1 - I_1^L)^\lambda, 1 - (1 - I_1^U)^\lambda\right] \\ \left[1 - (1 - F_1^L)^\lambda, 1 - (1 - F_1^U)^\lambda\right] \end{pmatrix}. \tag{8}$$

Definition 4 (see [11]). Let $x = ([T_1^L, T_1^U], [I_1^L, I_1^U], [F_1^L, F_1^U])$ and $y = ([T_2^L, T_2^U], [I_2^L, I_2^U], [F_2^L, F_2^U])$ be two interval neutrosophic numbers, and its operational rules satisfy the following operation relations:

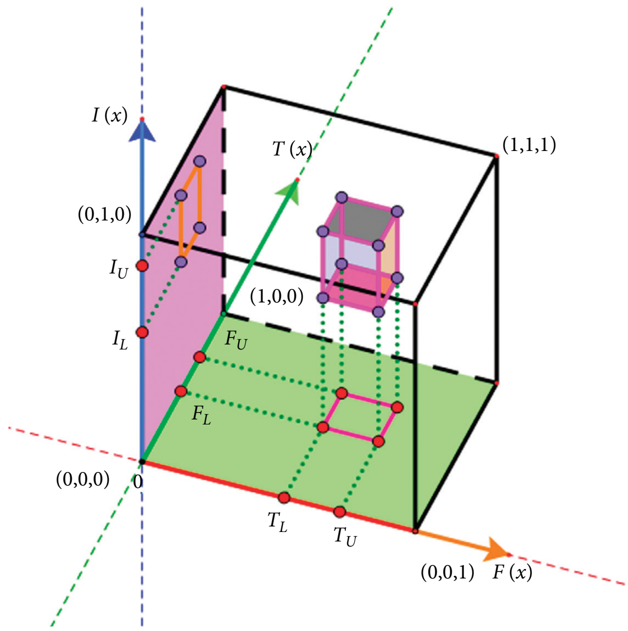

FIGURE 2: Geometric representation of the interval neutrosophic set.

(1) $x \oplus y = y \oplus x$

(2) $x \otimes y = y \otimes x$

(3) $\lambda(x \oplus y) = \lambda x \oplus \lambda y$, $\lambda \geq 0$

(4) $\lambda_1 x \oplus \lambda_2 x = (\lambda_1 + \lambda_2)x$, $\lambda_1, \lambda_2 \geq 0$

(5) $x^\lambda \oplus y^\lambda = (x \otimes y)^\lambda$, $\lambda \geq 0$

(6) $x^{\lambda_1} \otimes x^{\lambda_2} = x^{\lambda_1+\lambda_2}$, $\lambda_1, \lambda_2 \geq 0$

2.1.2. The Ranking Method of Interval Neutrosophic Numbers. Next, we introduce a method to compare the interval neutrosophic numbers, which fully considers the decision maker's attitude towards risk. We divide decision makers into three types: risk preference type, risk neutrality type, and risk aversion type. In the process of evaluation, whether qualitative or quantitative methods are used, objective facts should be taken as the basis as far as possible. Different attitudes of decision makers can lead to different results. Based on this, the definitions of expect function and fuzzy function are provided.

Definition 5. Let $x = ([T^L, T^U], [I^L, I^U], [F^L, F^U])$ be an INN, and then the expect function of an interval neutrosophic number can be defined as follows:

$$\mathrm{Exp}(x) = \frac{1}{2}\left(T^L - F^L + T^U - F^U\right) + \varphi\frac{1}{2}\left(2 - I^L - I^U\right), \quad 0 \leq \varphi \leq 1. \tag{9}$$

When the decision maker is the risk preference type, $0.5 < \varphi \leq 1$. When the decision maker is the risk aversion type, $0 \leq \varphi < 0.5$. When the decision maker is the risk neutrality type, $\varphi = 0.5$. Generally, we set $\varphi = 0.5$. We can compare the size of the interval neutrosophic numbers according to the size of the expected function. The greater the expected value of the INN, the greater the INN.

Here, we assume the decision maker is the risk neutrality type, and let $\varphi = 0.5$:

(1) Compare $M = ([0,4,0.6],[0.2,0.6],[0.2,0.5])$ and $N = ([0,3,0.7],[0.2,0.6],[0.3,0.6])$.
Because $\mathrm{Exp}(M) = 0.45$, $\mathrm{Exp}(N) = 0.35$, so $M > N$.

(2) Compare $M = ([0,3,0.7],[0.3,0.5],[0.3,0.6])$ and $N = ([0,3,0.7],[0.2,0.6],[0.3,0.6])$.
Because $\mathrm{Exp}(M) = 0.35$, $\mathrm{Exp}(N) = 0.35$, so $M = N$.

Obviously, M is less ambiguous, so we tend to think that M is more valuable. However, the abovementioned calculation results show that $M = N$, which is not consistent with the objective reality. Therefore, we propose a fuzzy function to assist in the comparison of the size of the interval neutrosophic numbers.

Definition 6. Let $M = ([T^L, T^U], [I^L, I^U], [F^L, F^U])$ be an interval neutrosophic number, then the fuzzy function of an interval neutrosophic number can be defined as follows:

$$\mathrm{Fuz}(M) = \left(T^U - T^L\right) \times \left(F^U - F^L\right) \times \left(I^U - I^L\right), \quad 0 \leq \mathrm{Fuz}(M) \leq 1. \tag{10}$$

Theorem 1. *The fuzzy function satisfies the following properties:*

(P1)
$\mathrm{Fuz}(M) = 1$, if $T^U = F^U = I^U = 1$, $T^L = F^L = I^L = 0$,

(P2) $\mathrm{Fuz}(M) = 0$, if $T^U = T^L$ or $F^U = F^L$ or $I^U = I^L$.

When the Exp (expect function) values of two INNs are equal, then compare their Fuz (fuzzy function) values. The INNs with smaller fuzzy function values have larger values.

With equation (10), we calculate the fuzzy values of M and N as follows:

$$\begin{aligned} \mathrm{Fuz}(M) &= 0.024, \\ \mathrm{Fuz}(N) &= 0.048. \end{aligned} \tag{11}$$

So, we can get $M > N$.

Let $M = ([T_M^L, T_M^U], [I_M^L, I_M^U], [F_M^L, F_M^U])$ *and* $N = ([T_N^L, T_N^U], [I_N^L, I_N^U], [F_N^L, F_N^U])$ be two neutrosophic numbers, and the ranking method of interval neutrosophic numbers are as follows:

(1) If $\mathrm{Exp}(M) > \mathrm{Exp}(N)$, then $M > N$

(2) If $\mathrm{Exp}(M) = \mathrm{Exp}(N)$, $\mathrm{Fuz}(M) > \mathrm{Fuz}(N)$, then $M < N$

(3) If $\mathrm{Exp}(M) = \mathrm{Exp}(N)$, $\mathrm{Fuz}(M) = \mathrm{Fuz}(N)$, then $M = N$

3. The Definition of Projection and Variation Entropy Weight

3.1. The Projection of Two Interval Neutrosophic Numbers. The main idea of the projection method is that each decision-making scheme is treated as a row vector, and then there is an angle between each alternative and the ideal solutions. The smaller the angle is, the more similar the two vectors are. The vector consists of direction and module. The angle cosine value between vectors mainly measures whether the direction of the two vectors is consistent but cannot reflect the size of their modules. Therefore, it is necessary to consider both the size of the module and the angle cosine in order to reflect the proximity between vectors. Based on this, the concept of projection is given.

This paper proposes a projection model based on INS, which not only retains the advantages of traditional projection methods but also has more flexibility and practicability in dealing with the uncertain information and inconsistent information.

Definition 7. Let $M = ([T_M^L, T_M^U], [I_M^L, I_M^U], [F_M^L, F_M^U])$ be an interval neutrosophic number,

$$|M| = \sqrt{\left(T_M^L\right)^2 + \left(T_M^U\right)^2 + \left(1 - I_M^L\right)^2 + \left(1 - I_M^U\right)^2 + \left(1 - F_M^L\right)^2 + \left(1 - F_M^U\right)^2}, \tag{12}$$

is called the modulus of interval neutrosophic, and $0 \le |M| \le \sqrt{6}$.

Definition 8. Let $M = ([T_M^L, T_M^U], [I_M^L, I_M^U], [F_M^L, F_M^U])$ and $N = ([T_N^L, T_N^U], [I_N^L, I_N^U], [F_N^L, F_N^U])$ be two INNs, and the inner product is

$$\begin{aligned} M \cdot N = {} & T_M^L T_N^L + T_M^U T_N^U + \left(1 - I_M^L\right)\left(1 - I_N^L\right) + \left(1 - I_M^U\right) \\ & \cdot \left(1 - I_N^U\right) + \left(1 - F_M^L\right)\left(1 - F_N^L\right) + \left(1 - F_M^U\right)\left(1 - F_N^U\right). \end{aligned} \tag{13}$$

Definition 9. Let $M = ([T_M^L, T_M^U], [I_M^L, I_M^U], [F_M^L, F_M^U])$ and $N = ([T_N^L, T_N^U], [I_N^L, I_N^U], [F_N^L, F_N^U])$ be two INNs, and the cosine of the angle between M and N is

$$\cos(M, N) = \frac{M \cdot N}{|M| \cdot |N|}. \tag{14}$$

It follows the following rules:

(1) $0 \le \cos(M, N) \le 1$,

(2) $\cos(M, N) = 1$, for $M = N$,

(3) $\cos(M, N) = \cos(N, M)$.

Definition 10. Let $M = ([T_M^L, T_M^U], [I_M^L, I_M^U], [F_M^L, F_M^U])$ and $N = ([T_N^L, T_N^U], [I_N^L, I_N^U], [F_N^L, F_N^U])$ be two interval neutrosophic numbers, and

$$\begin{aligned} \operatorname{proj}_N(M) &= |M| \cos(M, N) = |M| \frac{M \cdot N}{|M| \cdot |N|} = \frac{M \cdot N}{|N|} \\ &= \frac{T_M^L T_N^L + T_M^U T_N^U + \left(1 - I_M^L\right)\left(1 - I_N^L\right) + \left(1 - I_M^U\right)\left(1 - I_N^U\right) + \left(1 - F_M^L\right)\left(1 - F_N^L\right) + \left(1 - F_M^U\right)\left(1 - F_N^U\right)}{\sqrt{\left(T_N^L\right)^2 + \left(T_N^U\right)^2 + \left(1 - I_N^L\right)^2 + \left(1 - I_N^U\right)^2 + \left(1 - F_N^L\right)^2 + \left(1 - F_N^U\right)^2}}. \end{aligned} \tag{15}$$

is the projection of M on N, $0 \le \operatorname{proj}_N(M) \le \sqrt{6}$. Generally, the larger the value of $\operatorname{proj}_N(M)$ is, the closer M is to N, the smaller the value of $\operatorname{proj}_N(M)$ is, and the further the M away from N. When $M = ([0, 0], [1, 1], [1, 1])$ and $N = ([0, 0], [1, 1], [1, 1])$, we specify $\operatorname{proj}_N(M) = 1$.

The projection model with INNs is improved, in which positive information, antinegative information and antiuncertainty information are fused together instead of positive information, negative information, and uncertainty information.

3.2. The Variation Entropy of the Interval Neutrosophic Number. The basic idea of the entropy weight method is to determine the objective weight according to the variability of the indicator. Entropy is a main concept in the information theory and a measure of uncertainty. If experts take the form of INN as an evaluation value, it will bring a certain degree of uncertainty and fuzziness. Relative to the variation degree of a certain value to a group, we focus more on the ambiguity and uncertainty of the value. In view that the interval neutrosophic number takes the interval number to express the truth-membership, the indeterminacy-membership, and the falsity-membership, there may be great inconsistency in the data itself. Therefore, the weight of the indicator is determined by the accuracy of the data under a certain indicator. The law is that the lower the degree of fuzziness and uncertainty is, the greater the weight will be, while the higher the degree of fuzziness and uncertainty is, and the smaller the weight will be.

Definition 11. Let $M = ([T^L, T^U], [I^L, I^U], [F^L, F^U])$ be an interval neutrosophic number, and the variation entropy of the interval neutrosophic number (see Figure 3) is defined as follows:

$$E(M) = \left(T^U - T^L\right) \times \left(F^U - F^L\right) \times \frac{I^L + I^U}{2}. \tag{16}$$

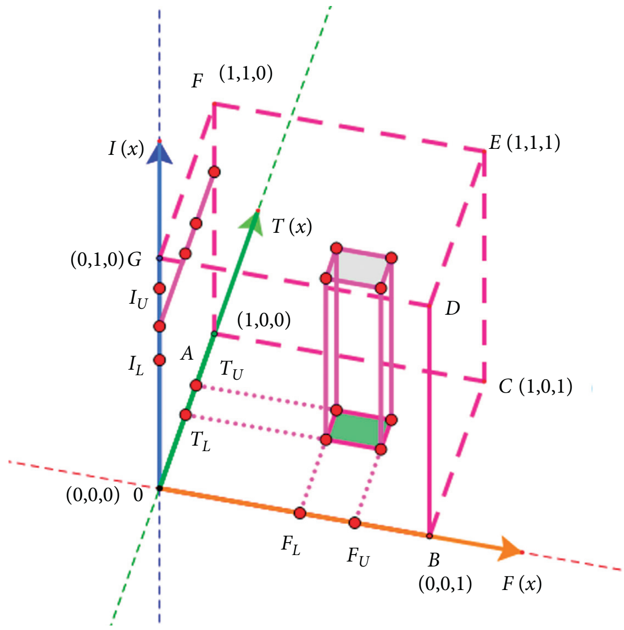

FIGURE 3: The geometric representation of the entropy for an interval neutrosophic number.

4. The Steps of Projection Methods Based on Improved Entropy and Interval Neutrosophic Set

Let $A = \{A_1, A_2, \ldots, A_m\}$ be the set of the alternatives, in which $A_i\,(i = 1, 2, \ldots, m)$ represents the ith alternative. Let $C = \{C_1, C_2, \ldots, C_n\}$ be the set of the attributes that are used to evaluate the alternatives, and here $C_j\,(j = 1, 2, \ldots, n)$ represents the jth attribute. Let $W = (w_1, w_2, \ldots, w_n)$ be a set of weights, w_j represents the weight of indicator C_j, $\sum_{j=1}^{n} w_j = 1, j = 1, 2, \ldots, n, \quad w_j \geq 0$. The decision matrix denoted by $X = [x_{ij}]_{m\times n}$, which is given by the experts. And x_{ij} represents the evaluation value of the ith alternative with respect to the jth attribute, and takes the form of INN:

$$X = \left[x_{ij}\right]_{m\times n} = \left[\left(\left[T_{ij}^L, T_{ij}^U\right], \left[I_{ij}^L, I_{ij}^U\right], \left[F_{ij}^L, F_{ij}^U\right]\right)\right]_{m\times n}. \quad (17)$$

As for the projection methods based on variation entropy and INS for MCDM, we will introduce the specific steps as follows.

Step 1: normalization of the decision matrix.

For multicriteria decision-making problems, different evaluation indicators often have different dimensions. In order to convert the elements of the decision matrix into the nondimensional form and eliminate the influence of different dimensions on decision-making results, according to equation (4), the decision information was transformed from the cost criteria to benefit criteria, and the decision matrix is normalized. According to the following methods, decision matrix $X = [x_{ij}]_{m\times n}$ is normalized as $R = [r_{ij}]_{m\times n}$:

$$r_{ij} = \begin{cases} x_{ij}, & \text{for benefit criteria,} \\ \overline{x}_{ij}, & \text{for cost criteria,} \end{cases} \quad (18)$$

where, according to equation (4), $\overline{x}_{ij}$ represents the inverse of x_{ij}.

Step 2: determine the weight of each indicator $W = (w_1, w_2, \ldots, w_n)$:

$$w_j = \frac{1/\sum_{i=1}^{m} E\left(r_{ij}\right)}{\sum_{j=1}^{n} 1/\sum_{i=1}^{m} E\left(r_{ij}\right)}, \quad (j = 1, 2, \ldots, n). \quad (19)$$

Step 3: the determination of positive and negative ideal solutions.

Decision making is a kind of subjective decision-making process. In addition to considering the uncertain information and fuzzy information in the problem domain, we should pay more attention to the attitude of decision makers towards uncertain information and fuzzy information, which reflects the attitude of decision makers towards risk.

4.1. The Common Approach. A common approach is to assume that decision makers are risk conservatives, who tend to avoid risk. If decision makers are conservative and pessimistic, then according to equations (20) and (21), the positive and negative ideal solutions can be defined as follows:

$$A^+ = \left\{\left[\max_i T_{ij}^L, \max_i T_{ij}^U\right], \left[\min_i I_{ij}^L, \min_i I_{ij}^U\right], \left[\min_i F_{ij}^L, \min_i F_{ij}^U\right]\right\}, \quad (20)$$

$$A^- = \left\{\left[\min_i T_{ij}^L, \min_i T_{ij}^U\right], \left[\max_i I_{ij}^L, \max_i I_{ij}^U\right], \left[\max_i F_{ij}^L, \max_i F_{ij}^U\right]\right\}. \quad (21)$$

4.2. The Improved Approach. Because decision makers have different attitudes towards indeterminacy and different expectations of risk, the results of positive and negative ideal solutions are different. According to equations (9) and (10), we rank the attribute values from big to small. Here, we can set the value of φ. The value of φ represents the attitude to the indeterminacy information. Then, according to equations (22) and (23), the formulas of positive and negative ideal solutions are as follows:

$$\widetilde{A}^{+} = \left\{\max_{i}\left(\left[T_{ij}^{L}, T_{ij}^{U}\right], \left[I_{ij}^{L}, I_{ij}^{U}\right], \left[F_{ij}^{L}, F_{ij}^{U}\right]\right)\right\}, \tag{22}$$

$$\widetilde{A}^{-} = \left\{\min_{i}\left(\left[T_{ij}^{L}, T_{ij}^{U}\right], \left[I_{ij}^{L}, I_{ij}^{U}\right], \left[F_{ij}^{L}, F_{ij}^{U}\right]\right)\right\}. \tag{23}$$

Step 4: calculating projections between alternatives and negative ideal solutions, respectively:

$$\operatorname{proj}_{A^{-}}(A_i) = \sum_{j=1}^{n} w_j \frac{T_{ij}^{L}T_{j}^{L-} + T_{ij}^{U}T_{j}^{U-} + \left(1 - I_{ij}^{L}\right)\left(1 - I_{j}^{L-}\right) + \left(1 - I_{ij}^{U}\right)\left(1 - I_{j}^{U-}\right) + \left(1 - F_{ij}^{L}\right)\left(1 - F_{j}^{L-}\right) + \left(1 - F_{ij}^{U}\right)\left(1 - F_{j}^{U-}\right)}{\sqrt{\left(T_{j}^{L-}\right)^2 + \left(T_{j}^{U-}\right)^2 + \left(1 - I_{j}^{L-}\right)^2 + \left(1 - I_{j}^{U-}\right)^2 + \left(1 - F_{j}^{L-}\right)^2 + \left(1 - F_{j}^{U-}\right)^2}}. \tag{24}$$

Step 5: rank the alternatives according to the value of $\operatorname{proj}_{A^{-}}(A_i)$. The bigger the value of $\operatorname{proj}_{A^{-}}(A_i)$, the worse the alternative. On the contrary, the smaller the value of C_i, the better the alternative.

5. Illustrative Example for Application of Software Quality-In-Use Evaluation

In the real world of software development and application, we have many methods to evaluate and improve software quality [55, 56]. Software quality evaluation is an effective way to improve software quality. The selection of evaluation criteria and methods is always the key problem in software quality evaluation. Suitable evaluation criteria and methods directly affect the quality of software evaluation. Software quality-in-use evaluation is an important part of software quality evaluation, and evaluation results provide reference for software quality evaluation. Since the evaluator may give the evaluation values involving the information of support, neutrality, and opposition, the interval neutrosophic number is suitable to be used as the expression form of the evaluation value. In the evaluation of software quality, it is difficult to determine the weight information. Therefore, in the face of unknown weight information, we tend to use the improved entropy weight determination method to determine the weight information according to the fuzziness and uncertainty of interval neutrosophic number.

Software quality-in-use use refers to the satisfaction extent of a software product to a specific user's specific needs in the user's environment during the utilization. Software quality-in-use mainly judges the quality of software from the perspective of users, which is quite different from the software quality we used to say. Its focus is on the satisfaction of users about software itself, instead of the performance and function of software. As the supporting hardware and running environment of users are different from those of developers, the evaluation results may change. An enterprise needs to evaluate the software quality-in-use according to four criteria of effectiveness $C1$, productivity and satisfaction $C2$, and risk $C3$, and we need to select the software with better software quality-in-use. After the preliminary screening, there are six alternatives $A1$, $A2$, $A3$, $A4$, $A5$, and $A6$ to choose from. In order to evaluate the quality-in-use of software scientifically and reasonably, the interval neutrosophic number was employed to express the evaluation values of each criteria. The evaluation values of experts for each alternative under different attributes are shown in Table 1.

(1) The decision matrix A is normalized according to equations (4) and (18). Since risk is a cost-oriented attribute, the normalized matrix R is shown in Table 2.

(2) According to equations (16) and (19), calculate the weight of each indicator:

$$W = (0.32, 0.44, 0.24). \tag{25}$$

(3) If decision makers are conservative and pessimistic, the common approach is adopted. According to equations (20) and (21), determine the positive and negative ideal solutions:

$$\begin{aligned} A^{+} = &(([0.5, 0.7], [0.1, 0.2], [0.2, 0.3]), ([0.6, 0.8], \\ &[0.2, 0.4], [0.1, 0.3]), ([0.7, 0.9], [0.1, 0.5], \\ &[0.1, 0.4])), \\ A^{-} = &(([0.1, 0.3], [0.7, 0.8], [0.5, 0.9]), ([0.2, 0.5], \\ &[0.5, 0.7], [0.5, 0.6]), ([0.2, 0.5], [0.6, 0.9], \\ &[0.7, 0.9])). \end{aligned} \tag{26}$$

If we consider decision maker's different attitude to risk, the improved approach is adopted. According to equations (22) and (23), determine the positive and negative ideal solutions:

$$\begin{aligned} \widetilde{A}^{+} = &(([0.4, 0.6], [0.3, 0.5], [0.4, 0.7]), ([0.5, 0.8], \\ &[0.3, 0.4], [0.2, 0.4]), ([0.2, 0.6], [0.3, 0.5], \\ &[0.1, 0.4])), \\ \widetilde{A}^{-} = &(([0.2, 0.4], [0.7, 0.8], [0.3, 0.4]), ([0.3, 0.5], \\ &[0.4, 0.7], [0.5, 0.6]), ([0.2, 0.5], [0.3, 0.8], \\ &[0.5, 0.7])). \end{aligned} \tag{27}$$

Table 1: Decision matrix given by experts.

Alternatives	Effectiveness ($C1$)	Productivity and satisfaction ($C2$)	Risk ($C3$)
$A1$	([0.4, 0.6], [0.3, 0.5], [0.4, 0.7])	([0.5, 0.8], [0.3, 0.4], [0.2, 0.4])	([0.5, 0.7], [0.2, 0.7], [0.2, 0.5])
$A2$	([0.2, 0.4], [0.7, 0.8], [0.3, 0.4])	([0.6, 0.7], [0.4, 0.5], [0.4, 0.5])	([0.2, 0.5], [0.1, 0.9], [0.4, 0.6])
$A3$	([0.5, 0.7], [0.6, 0.8], [0.2, 0.4])	([0.4, 0.6], [0.2, 0.5], [0.2, 0.6])	([0.3, 0.4], [0.3, 0.5], [0.2, 0.5])
$A4$	([0.3, 0.6], [0.3, 0.7], [0.5, 0.9])	([0.3, 0.5], [0.4, 0.7], [0.5, 0.6])	([0.2, 0.8], [0.3, 0.4], [0.5, 0.6])
$A5$	([0.2, 0.5], [0.1, 0.5], [0.2, 0.3])	([0.6, 0.7], [0.3, 0.4], [0.4, 0.6])	([0.7, 0.9], [0.2, 0.6], [0.7, 0.9])
$A6$	([0.1, 0.3], [0.1, 0.2], [0.5, 0.8])	([0.2, 0.5], [0.5, 0.7], [0.1, 0.3])	([0.1, 0.4], [0.5, 0.7], [0.2, 0.6])

Table 2: Normalized decision matrix.

Alternatives	Effectiveness ($C1$)	Productivity and satisfaction ($C2$)	Risk ($C3$)
$A1$	([0.4, 0.6], [0.3, 0.5], [0.4, 0.7])	([0.5, 0.8], [0.3, 0.4], [0.2, 0.4])	([0.2, 0.5], [0.3, 0.8], [0.5, 0.7])
$A2$	([0.2, 0.4], [0.7, 0.8], [0.3, 0.4])	([0.6, 0.7], [0.4, 0.5], [0.4, 0.5])	([0.4, 0.6], [0.1, 0.9], [0.2, 0.5])
$A3$	([0.5, 0.7], [0.6, 0.8], [0.2, 0.4])	([0.4, 0.6], [0.2, 0.5], [0.2, 0.6])	([0.2, 0.5], [0.5, 0.7], [0.3, 0.4])
$A4$	([0.3, 0.6], [0.3, 0.7], [0.5, 0.9])	([0.3, 0.5], [0.4, 0.7], [0.5, 0.6])	([0.5, 0.6], [0.6, 0.7], [0.2, 0.8])
$A5$	([0.2, 0.5], [0.1, 0.5], [0.2, 0.3])	([0.6, 0.7], [0.3, 0.4], [0.4, 0.6])	([0.7, 0.9], [0.4, 0.8], [0.7, 0.9])
$A6$	([0.1, 0.3], [0.1, 0.2], [0.5, 0.8])	([0.2, 0.5], [0.5, 0.7], [0.1, 0.3])	([0.2, 0.6], [0.3, 0.5], [0.1, 0.4])

(4) When decision makers adopt the common approach, according to equation (24), calculate projections between alternatives and negative ideal solutions:

$$\begin{aligned} \mathrm{proj}_{A^-}(A1) &= 1.358, \\ \mathrm{proj}_{A^-}(A2) &= 1.256, \\ \mathrm{proj}_{A^-}(A3) &= 1.297, \\ \mathrm{proj}_{A^-}(A4) &= 1.090, \\ \mathrm{proj}_{A^-}(A5) &= 1.396, \\ \mathrm{proj}_{A^-}(A6) &= 1.273. \end{aligned} \tag{28}$$

When decision makers adopt the improved approach, we assume decision makers are the risk aversion type. So, let $\varphi = 0.5$, according to equation (24), calculate projections between alternatives and negative ideal solutions:

$$\begin{aligned} \mathrm{proj}_{\widetilde{A}^-}(A1) &= 1.354, \\ \mathrm{proj}_{\widetilde{A}^-}(A2) &= 1.215, \\ \mathrm{proj}_{\widetilde{A}^-}(A3) &= 1.225, \\ \mathrm{proj}_{\widetilde{A}^-}(A4) &= 1.068, \\ \mathrm{proj}_{\widetilde{A}^-}(A5) &= 1.365, \\ \mathrm{proj}_{\widetilde{A}^-}(A6) &= 1.357. \end{aligned} \tag{29}$$

(5) When decision adopts the common approach, rank the alternatives according to the value of proj_{A^-}:

$$\begin{aligned} &\mathrm{proj}_{A^-}(A4) < \mathrm{proj}_{A^-}(A2) < \mathrm{proj}_{A^-}(A6) \\ &\quad < \mathrm{proj}_{A^-}(A3) < \mathrm{proj}_{A^-}(A1) < \mathrm{proj}_{A^-}(A5). \end{aligned} \tag{30}$$

So, the rank results of alternatives are as follows:

$$A4 > A2 > A6 > A3 > A1 > A5. \tag{31}$$

According to the evaluation results, we tend to think $A4$ has better quality-in-use.

(6) When decision adopts the improved approach, rank the alternatives according to the value of proj_{A^-}:

$$\begin{aligned} &\mathrm{proj}_{A^-}(A4) < \mathrm{proj}_{A^-}(A2) < \mathrm{proj}_{A^-}(A3) < \mathrm{proj}_{A^-}(A1) \\ &\quad < \mathrm{proj}_{A^-}(A6) < \mathrm{proj}_{A^-}(A5). \end{aligned} \tag{32}$$

So, the rank results of alternatives are as follows:

$$A4 > A2 > A3 > A1 > A6 > A5. \tag{33}$$

According to the evaluation results, we also tend to think $A4$ has better quality-in-use.

Besides, we also use the TOPSIS method with Hamming distance or Euclidean distance to evaluate the data listed in Table 2. We get the ranking results, as shown in Table 3. The results show that the projection method gets the similar results with the TOPSIS method.

In the evaluation with INNs, we find that there is such information in reality, if it is expressed by INNs, such as ([0.12, 0.13], [0.05, 0.09], and [0.07, 0.12]). The characteristic of this kind of information is that the values of the three parameters are very small and close. Is this kind of information valuable or negligible in our decision-making? This is what we should think about. First of all, we should consider the amount of information provided by this value denoted by $\mathrm{Inf}(x) = (T^L + T^U + I^L + I^U + F^L + F^U)/6$. According to the value of $\mathrm{Inf}(x)$, we consider whether other evaluation values of the same attribute also have a small amount of information. If so, this is a normal phenomenon and will be handled according to the normal process. Otherwise, we can take two schemes: first, take it as valuable

Table 3: Ranking results according to different methods.

Methods	Ranking results
Topsis (Hamming distance)	$A4 > A2 > A6 > A3 > A1 > A5$
Topsis (Euclidean distance)	$A4 > A2 > A3 > A6 > A1 > A5$
Projection method (common ideal solutions determine method)	$A4 > A2 > A6 > A3 > A1 > A5$
Projection method (improved solutions determine method)	$A4 > A2 > A3 > A1 > A6 > A5$

information and assign it a larger weight according to the entropy weight theory; second, take it as an invalid value and exclude it from the decision-making process.

Besides, in the future research, we will consider the uncertainty and fuzziness of INNs as well as its variation to the group, further improve the calculation formula of entropy weight, and apply the improved entropy weight formula to main kinds of MCDM methods.

6. Conclusions

This paper firstly introduced and quoted some basic operational rules of INNs, then defined the projection of two INNs, improved the entropy weight formula for INNs, and introduced a new ranking method for INNs. Based on this, this paper further proposed an MCDM approach based on the projection method for INNs, which has the following characteristics: (1) the projection model with INNs is improved, in which the positive information, the antinegative information, and the antiuncertainty information are fused together instead of the positive information, the negative information, and the uncertainty information; (2) it introduced the improved entropy of an INN and proposed the improved entropy weight formula; (3) it made the decision-making results more flexible and reliable because it determined the positive and negative ideal solutions according to the decision maker's attitude to risk.

The research results in this paper not only enrich the theoretical contents of the INSs but also provide a new way for the MCDM problems, which provides a sufficient scientific basis for us to solve multicriteria group decision-making problems. However, in this paper, we only considered the application of the MCDM method based on the projection model in solving the software quality-in-use evaluation problems. The future research work is mainly divided into two aspects: on the one hand, we will continue to promote the application of this method in related fields, such as software outsourcing service provider selection, information security assessment, and software product quality assessment, especially for the evaluation of external and internal software quality; on the other hand, we will continue to study the combination between INNs and theoretical methods, such as two-sided matching model [57], TODIM method, and the prospect theory.

Data Availability

The data of this manuscript are available, and everyone can freely access the data supporting the conclusion of the study.

Conflicts of Interest

The author declareS that there are no conflicts of interest.

References

[1] L. A. Zadeh, "Fuzzy sets," *Information and Control*, vol. 8, no. 3, pp. 338–353, 1965.

[2] K. T. Atanassov, "Intuitionistic fuzzy sets," *Fuzzy Sets and Systems*, vol. 20, no. 1, pp. 87–96, 1986.

[3] K. Atanassov and G. Gargov, "Interval valued intuitionistic fuzzy sets," *Fuzzy Sets and Systems*, vol. 31, no. 3, pp. 343–349, 1989.

[4] F. Smarandache, *A Unifying Field in Logics. Neutrosophy: Neutrosophicprobability, Set and Logic*, American Research Press, Rehoboth, NM, USA, 1999.

[5] H. B. Wang, F. Smarandache, Y. Q. Zhang, and R. Sunderraman, "Single valued neutrosophic sets," *Multispace and Multistructure*, vol. 4, pp. 410–413, 2010.

[6] H. Wang, F. Smarandache, Y. Q. Zhang, and R. Sunderraman, *Interval Neutrosophic Sets and Logic: Theory and Applications in Computing*, Hexis, Phoenix, AZ, USA, 2005.

[7] J. Ye, "Single valued neutrosophic cross-entropy for multicriteria decision making problems," *Applied Mathematical Modelling*, vol. 38, no. 3, pp. 1170–1175, 2014.

[8] D. J. Yu, Z. S. Xu, and W. R. Wang, "A bibliometric analysis of fuzzy optimization and decision making (2002–2017)," *Fuzzy Optimization and Decision Making*, vol. 18, no. 3, pp. 371–397, 2019.

[9] D. Yu, Z. Xu, and J. Šapauskas, "The evolution of "Technological and Economic Development of Economy": a bibliometric analysis," *Technological and Economic Development of Economy*, vol. 25, no. 3, pp. 369–385, 2019.

[10] D. J. Yu, Z. S. Xu, and X. Z. Wang, "Bibliometric analysis of support vector machines research trend: a case study in China," *International Journal of Machine Learning and Cybernetics*, vol. 11, pp. 715–718, 2020.

[11] P. Majumdar and S. K. Samanta, "On similarity and entropy of neutrosophic sets," *Journal of Intelligent & Fuzzy Systems*, vol. 26, no. 3, pp. 1245–1252, 2014.

[12] C. Kahraman and İ. Otay, *Fuzzy Multi-Criteria Decision-Making Using Neutrosophic Sets*, Springer, Berlin, Germany, 2019.

[13] H. Wu, Y. Yuan, L. Wei, and L. Pei, "On entropy, similarity measure and cross-entropy of single-valued neutrosophic sets and their application in multi-attribute decision making," *Soft Computing*, vol. 22, no. 22, pp. 7367–7376, 2018.

[14] J. Ye, "Multicriteria decision-making method using the correlation coefficient under single-valued neutrosophic environment," *International Journal of General Systems*, vol. 42, no. 4, pp. 386–394, 2013.

[15] P. D. Liu and Y. M. Wang, "Multiple attribute decision-making method based on single-valued neutrosophic normalized weighted Bonferroni mean," *Neural Computing and Applications*, vol. 25, no. 7-8, pp. 2001–2010, 2014.

[16] S. Ashraf, S. Abdullah, F. Smarandache, and N. Amin, "Logarithmic hybrid aggregation operators based on single valued neutrosophic sets and their applications in decision support systems," *Symmetry*, vol. 11, no. 3, pp. 364–387, 2019.
[17] F. Karaaslan and K. Hayat, "Some new operations on single-valued neutrosophic matrices and their applications in multi-criteria group decision making," *Applied Intelligence*, vol. 48, no. 12, pp. 4594–4614, 2018.
[18] J. Ye, "A multicriteria decision-making method using aggregation operators for simplified neutrosophic sets," *Journal of Intelligent & Fuzzy Systems*, vol. 26, no. 5, pp. 2459–2466, 2014.
[19] 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.
[20] F. Karaaslan, "Multicriteria decision-making method based on similarity measures under single-valued neutrosophic refined and interval neutrosophic refined environments," *International Journal of Intelligent Systems*, vol. 33, no. 5, pp. 928–952, 2018.
[21] H. B. Wang, F. Smarandache, Y. Q. Zhang, and R. Sunderraman, "Interval neutrosophic logic," *Advances in Fuzzy Sets and Systems*, vol. 1, no. 3, pp. 187–218, 2006.
[22] Ş. Ridvan, "Cross-entropy measure on interval neutrosophic sets and its applications in multicriteria decision making," *Neural Computing and Applications*, vol. 28, no. 5, pp. 1177–1187, 2017.
[23] Z.-P. Tian, H.-Y. Zhang, J. Wang, J.-Q. Wang, and X.-H. Chen, "Multi-criteria decision-making method based on a cross-entropy with interval neutrosophic sets," *International Journal of Systems Science*, vol. 47, no. 15, pp. 3598–3608, 2016.
[24] J. Ye, "Similarity measures between interval neutrosophic sets and their applications in multicriteria decision-making," *Journal of Intelligent & Fuzzy Systems*, vol. 26, no. 1, pp. 165–172, 2014.
[25] E. Bolturk and C. Kahraman, "A novel interval-valued neutrosophic AHP with cosine similarity measure," *Soft Computing*, vol. 22, no. 15, pp. 4941–4958, 2018.
[26] H.-X. Sun, H.-X. Yang, J.-Z. Wu, and Y. Ouyang, "Interval neutrosophic numbers choquet integral operator for multi-criteria decision making," *Journal of Intelligent & Fuzzy Systems*, vol. 28, no. 6, pp. 2443–2455, 2015.
[27] H. X. Zhang, J. Q. Wang, and X. H. Chen, "An outranking approach for multi-criteria decision-making problems with interval-valued neutrosophic sets," *Neural Computing and Applications*, vol. 27, no. 3, pp. 615–627, 2016.
[28] H. Y. Zhang, J. Q. Wang, and X. H. Chen, "Interval neutrosophic sets and their application in multicriteria decision making problems," *The Scientific World Journal*, vol. 2014, Article ID 645953, 15 pages, 2014.
[29] P. Liu and X. You, "Interval neutrosophic muirhead mean operators and their application in multiple attribute group decision-making," *International Journal for Uncertainty Quantification*, vol. 7, no. 4, pp. 303–334, 2017.
[30] L. P. Zhou, J. Y. Dong, and S. P. Wan, "Two new approaches for multi-attribute group decision-making with interval-valued neutrosophic frank aggregation operators and incomplete weights," *IEEE ACCESS*, vol. 7, pp. 2169–3536, 2019.
[31] H. Yang, X. Wang, and K. Qin, "New similarity and entropy measures of interval neutrosophic sets with applications in multi-attribute decision-making," *Symmetry*, vol. 11, no. 3, p. 370, 2019.
[32] S. Dalapati, S. Pramanik, S. Alam, F. Smarandache, and T. K. Roy, "IN-cross entropy based MAGDM strategy under interval neutrosophic set environment," *Neutrosophic Sets and Systems*, vol. 18, pp. 43–57, 2017.
[33] K. Mondal, S. Pramanik, and B. C. Giri, "Interval neutrosophic tangent similarity measure based MADM strategy and its application to MADM problems," *Neutrosophic Sets and Systems*, vol. 19, pp. 47–56, 2018.
[34] P. P. Dey, S. Pramanik, and B. C. Giri, "An extended grey relational analysis based interval neutrosophic multi-attribute decision making for weaver selection," *Journal of New Theory*, no. 9, pp. 82–93, 2015.
[35] J. Ye, "Operations and aggregation method of neutrosophic cubic numbers for multiple attribute decision-making," *Soft Computing*, vol. 22, no. 22, pp. 7435–7444, 2018.
[36] Z. Lu and J. Ye, "Cosine measures of neutrosophic cubic sets for multiple attribute decision-making," *Symmetry*, vol. 9, no. 7, p. 121, 2017.
[37] P. D. Liu, Q. Khan, and T. Mahmood, "Group decision making based on power Heronian aggregation operators under neutrosophic cubic environment," *Soft Computing*, vol. 23, no. 3, 2020, in Press.
[38] S. Pramanik, S. Dalapati, S. Alam, F. Smarandache, and T. K. Roy, "NC-cross entropy based MADM strategy in neutrosophic cubic set environment," *Mathematics*, vol. 6, no. 5, p. 67, 2018.
[39] S. Pramanik, S. Dalapati, S. Alam, and T. K. Roy, "NC-VIKOR based MAGDM strategy under neutrosophic cubic set environment," *Neutrosophic Sets and Systems*, vol. 20, pp. 95–108, 2018.
[40] S. Ashraf, T. Mahmood, S. Abdullah, and Q. Khan, "Different approaches to multi-criteria group decision making problems for picture fuzzy environment," *Bulletin of the Brazilian Mathematical Society, New Series*, vol. 50, no. 2, pp. 373–397, 2019.
[41] S. Zeng, S. Asharf, M. Arif, and S. Abdullah, "Application of exponential Jensen picture fuzzy divergence measure in multi-criteria group decision making," *Mathematics*, vol. 7, no. 2, p. 191, 2019.
[42] P. Liu, T. Mahmood, and Q. Khan, "Group decision making based on power Heronian aggregation operators under linguistic neutrosophic environment," *International Journal of Fuzzy Systems*, vol. 20, no. 3, pp. 970–985, 2018.
[43] F. Karaaslan, "Gaussian single-valued neutrosophic numbers and its application in multi-attribute decision making," *Neutrosophic Sets and Systems*, vol. 22, pp. 101–117, 2018.
[44] C. Jana, M. Pal, F. Karaaslan, and J. Q. Wang, "Trapezoidal neutrosophic aggregation operators and its application in multiple attribute decision making process," *Scientica Iranica*, 2018, in Press.
[45] S. Pramanik, P. Biswas, and B. C. Giri, "Hybrid vector similarity measures and their applications to multi-attribute decision making under neutrosophic environment," *Neural Computing and Applications*, vol. 28, no. 5, pp. 1163–1176, 2017.
[46] S. Ashraf, S. Abdullah, T. Mahmood, F. Ghani, and T. Mahmood, "Spherical fuzzy sets and their applications in multi-attribute decision making problems," *Journal of Intelligent & Fuzzy Systems*, vol. 36, no. 3, pp. 2829–2844, 2019.
[47] S. Ashraf and S. Abdullah, "Spherical aggregation operators and their application in multiattribute group decision-making," *International Journal of Intelligent Systems*, vol. 34, no. 3, pp. 493–523, 2019.

[48] S. Ashraf, S. Abdullah, and T. Mahmood, “GRA method based on spherical linguistic fuzzy choquet integral environment and its application in multi-attribute decision-making problems,” *Mathematical Sciences*, vol. 12, no. 4, pp. 263–275, 2018.

[49] S. Ashraf, S. Abdullah, and T. Mahmood, “Spherical fuzzy Dombi aggregation operators and their application in group decision making problems,” *Journal of Ambient Intelligence and Humanized Computing*, 2019, in Press.

[50] S. Ashraf, S. Abdullah, M. Aslam, M. Qiyas, and M. A. Kutbi, “Spherical fuzzy sets and its representation of spherical fuzzy t-norms and t-conorms,” *Journal of Intelligent & Fuzzy Systems*, vol. 36, no. 6, pp. 6089–6102, 2019.

[51] H. Jin, S. Ashraf, S. Abdullah, M. Qiyas, M. Bano, and S. Zeng, “Linguistic spherical fuzzy aggregation operators and their applications in multi-attribute decision making problems,” *Mathematics*, vol. 7, no. 5, p. 413, 2019.

[52] Y. Jin, S. Ashraf, and S. Abdullah, “Spherical fuzzy logarithmic aggregation operators based on entropy and their application in decision support systems,” *Entropy*, vol. 21, no. 7, p. 628, 2019.

[53] M. Rafiq, S. Ashraf, S. Abdullah, T. Mahmood, and S. Muhammad, “The cosine similarity measures of spherical fuzzy sets and their applications in decision making,” *Journal of Intelligent & Fuzzy Systems*, vol. 36, no. 6, pp. 6059–6073, 2019.

[54] S. Ashraf, S. Abdullah, and L. Abdullah, “Child development influence environmental factors determined using spherical fuzzy distance measures,” *Mathematics*, vol. 7, no. 8, p. 661, 2019.

[55] W. Pan, B. Li, J. Liu, Y. Ma, and B. Hu, “Analyzing the structure of Java software systems by weighted *K*-core decomposition,” *Future Generation Computer Systems*, vol. 83, pp. 431–444, 2018.

[56] W. Pan, B. Song, K. Li, and K. Zhang, “Identifying key classes in object-oriented software using generalized *k*-core decomposition,” *Future Generation Computer Systems*, vol. 81, pp. 188–202, 2018.

[57] D. J. Yu and Z. S. Xu, “Intuitionistic fuzzy two-sided matching model and its application to personnel-position matching problems,” *Journal of the Operational Research Society*, vol. 71, no. 2, 2020, in Press.