Algorithms for neutrosophic soft decision making based on EDAS, new similarity measure and level soft set

Xindong Peng,∗ and Chong Li
a School of Information Science and Engineering, Shaoguan University, Shaoguan, China
b College of Command Information System, PLA University of Science and Technology, Nanjing, China

Abstract. This paper presents three novel single-valued neutrosophic soft set (SVNSS) methods. First, we initiate a new axiomatic definition of single-valued neutrosophic similarity measure, which is expressed by single-valued neutrosophic number (SVNN) that will reduce the information loss and remain more original information. Then, the objective weights of various parameters are determined via grey system theory. Moreover, we develop the combined weights, which can show both the subjective information and the objective information. Later, we propose three algorithms to solve single-valued neutrosophic soft decision making problem by Evaluation based on Distance from Average Solution (EDAS), similarity measure and level soft set. Finally, the effectiveness and feasibility of approaches are demonstrated by a numerical example.

Keywords: Single-valued neutrosophic soft set, similarity measure, SVNN, Combined weighed, EDAS, level soft set

1. Introduction


Smarandache [17] initially presented the concept of a neutrosophic set from a philosophical point of view. A neutrosophic set is characterized by a truth-membership degree, an indeterminacy-membership degree, and a falsity-membership degree. It generalizes the concept of the classic set, fuzzy set [2], interval-valued fuzzy set [4], paraconsistent set [17],
and tautological set [17]. From scientific or engineering point of view, the neutrosophic set and set-theoretic operators need to be specified. Otherwise, it will be difficult to apply in the real applications. Hence, Smarandache [17] firstly introduced the a single valued neutrosophic set (SVNS). Wang et al. [18] provided the set-theoretic operators and various properties of SVNSs. Ye [19, 20] proposed a multi-attribute decision making (MADM) method using the correlation coefficient under single-valued neutrosophic environment. Ye [21, 22] further developed clustering method and decision making methods by similarity measures of SVNS. Meanwhile, Peng and Dai [23] presented new similarity measure of SVNS and applied them to decision making. Biswas et al. [24] extended the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) method for multi-attribute single-valued neutrosophic decision-making problem. Sahin and Kucuk [25] defined a subethod measure for SVNS, and applied to MADM. Yang et al. [26] introduced single valued neutrosophic relations and discussed their properties. Huang [27] developed a new distance measure of SVNSs, and applied them to clustering analysis and MADM. Liu [28] proposed aggregation operators based on Archimedean t-conorm and t-norm for SVNS and also gave an application in MADM. Wu et al. [29] proposed a cross-entropy and prioritized aggregation operator with simplified neutrosophic sets. Single valued neutrosophic graphs [30–32] and bipolar single valued neutrosophic graphs [33, 34] are proposed by Broumi et al. Peng et al. [35, 36] proposed ELECTRE approach and qualitative flexible approach based on likelihood for multi-valued neutrosophic MADM problem, respectively. Ji et al. [37] introduced a projection-based TODIM method for multi-valued neutrosophic MADM problem. Tian et al. [38] presented an improved MULTIMOORA approach for simplified neutrosophic linguistic set. Later, Tian et al. [39] incorporated power aggregation operators and a TOPSIS-based QUALIFLEX method in order to solve green product design selection problems using simplified neutrosophic linguistic information. Tian et al. [40] proposed a MADM based on generalized prioritized aggregation operators under simplified neutrosophic uncertain linguistic environment.


Evaluation based on Distance from Average Solution (EDAS), originally proposed by Ghorabaee et al. [47], is a new MADM method for inventory ABC classification. It is very useful when we have some conflicting parameters. In the compromise MADM methods such as TOPSIS and VIKOR [48], the best alternative is got by computing the distance from ideal and nadir solutions. The desirable alternative has lower distance from ideal solution and higher distance from nadir solution in these MADM methods. Ghorabaee et al. [49] extended the EDAS method to supplier selection. As far as we know, however, the study of the MADM problem based on EDAS method have not been reported in the existing academic literature. Hence, it is an interesting research topic to apply the EDAS in MADM to rank and determine the best alternative under single-valued neutrosophic soft environment. Through a comparison analysis of the given methods, their objective evaluation is carried out, and the method which maintains consistency of its results is chosen.

For computing the similarity measure of two SVNSs, we propose a new axiomatic definition of similarity measure, which takes in the form of SVNN. Comparing with the existing literature [21, 22, 42, 43], our similarity measure can remain more original decision information.

By means of level soft sets, Feng et al. [7] presented an adjustable approach to fuzzy soft sets based decision making. By considering different types of thresholds, it can derive different level soft sets from the original fuzzy soft set. In general, the final optimal decisions based on different level soft sets could be different. Thus the newly proposed approach is in fact an adjustable method which captures an important feature for decision making in an imprecise environment: some of these problems are essentially humanistic and thus subjective in nature. As far as we know, however, the study of the single-valued neutrosophic soft MADM problem based on level soft set have not been reported in the existing academic literature.
Considering that different attribute weights will influence the ranking results of alternatives, we develop a new method to determine the attribute weights by combining the subjective elements with the objective ones. This model is different from the existing methods, which can be divided into two tactics: one is the subjective weighting evaluation methods and the other is the objective weighting determine methods, which can be computed by grey system theory [50]. The subjective weighting methods focus on the preference information of the decision maker [19–21, 27–29], while they ignore the objective information. The objective weighting determine methods do not take the preference of the decision maker into account, that is to say, these methods fail to take the risk attitude of the decision maker into account [22, 24]. The feature of our weighting model can show both the subjective information and the objective information. Hence, combining objective weights with subjective weights, a combined model to obtain attribute weights is proposed.

The remainder of this paper is organized as follows: In Section 2, we review some fundamental conceptions of neutrosophic sets, single-valued neutrosophic sets, soft set and single-valued neutrosophic soft sets. In Section 3, a new axiomatic definition of single-valued neutrosophic similarity measure is presented. In Section 4, three single-valued neutrosophic soft decision making approaches based on EDAS, similarity measure and level soft set are shown. In Section 5, a numerical example is given to illustrate the proposed methods. The paper is concluded in Section 6.

2. Preliminaries

2.1. Neutrosophic set

Neutrosophic set is a portion of neutrosophy, which researches the origin, and domain of neutralities, as well as their interactions with diverse ideational scope [17], and is a convincing general formal framework, which extends the presented sets [2, 4] from philosophical point. Smarandache [17] introduced the definition of neutrosophic set as follows:

**Definition 1.** [17] Let $X$ be a universe of discourse, with a class of elements in $X$ denoted by $x$. A 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 $F_N(x)$. The functions $T_N(x), I_N(x)$, and $F_N(x)$ are real standard or non-standard subsets of $[0^-, 1^+]$. That is $T_N(x): X \rightarrow [0^-, 1^+]$, $I_N(x): X \rightarrow [0^-, 1^+]$, and $F_N(x): X \rightarrow [0^-, 1^+]$.

There is restriction on the sum of $T_N(x), I_N(x)$, and $F_N(x)$, so $0^- \leq \sup T_N(x) + \sup I_N(x) + \sup F_N(x) \leq 3^+$. As mentioned above, it is hard to apply the neutrosophic set to solve some real problems. Hence, Smarandache [17] presented SVNS, which is a subclass of the neutrosophic set and mentioned the definition as follows:

**Definition 2.** [17] Let $X$ be a universe of discourse, 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:

$$N = \{ < x, T_N(x), I_N(x), F_N(x) > | x \in X \},$$

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 $0 \leq T_N(x) + I_N(x) + F_N(x) \leq 3$. For a SVNS $N$ in $X$, the triplet $(T_N(x), I_N(x), F_N(x))$ is called single-valued neutrosophic number (SVNN). For convenience, we can simply use $x = (T_x, I_x, F_x)$ to represent a SVNN as an element in the SVNS $N$.

Generally speaking, two special values are taken into consideration, i.e., SVNN 0 and 1. If we think about 0 as the worst value and 1 as the best value, we can set 0 as $(0,1,1)$ and 1 as $(1,0,0)$.

**Definition 3.** [17, 18] 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. $x \cup y = (\max\{T_x, T_y\}, \min\{I_x, I_y\}, \min \{F_x, F_y\})$;
3. $x \cap y = (\min\{T_x, T_y\}, \max\{I_x, I_y\}, \max \{F_x, F_y\})$;
4. $x \oplus y = (T_x + T_y - T_x \cdot T_y, I_x \cdot I_y, F_x \cdot F_y)$;
5. $x \ominus y = (T_x - T_y, I_x + I_y - I_x \cdot I_y, F_x + F_y - F_x \cdot F_y)$;
6. $\lambda x = (1 - (1 - T_x)\lambda, (1 - I_x)\lambda, (1 - F_x)\lambda), \lambda > 0$;
7. $x^\lambda = ((T_x)^\lambda, (1 - (1 - I_x)^\lambda, 1 - (1 - F_x)^\lambda), \lambda > 0$. 

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For comparing two SVNNs, Peng et al. [51] introduced a similarity measure method for a SVNN.

**Definition 4.** [51] Let \( x = (T_x, I_x, F_x) \) be a SVNN, then the score function \( s(x) \) is defined as follows:

\[
s(x) = \frac{2}{3} + \frac{T_x}{3} - \frac{I_x}{3} - \frac{F_x}{3}.
\]

It measures the hamming similarity between \( x = (T_x, I_x, F_x) \) and the ideal solution \((1, 0, 0)\) for the comparison of SVNNs.

**Definition 5.** [28] Let \( x_j (j = 1, 2, \cdots, n) \) be a series of the SVNNs, and \( w = (w_1, w_2, \cdots, w_n)^T \) be the weight vector of \( x_j (i = 1, 2, \cdots, n) \), then a single-valued neutrosophic weighted averaging (SVNWA) operator is a mapping SVNWA: \( X^n \rightarrow X \), where

\[
\text{SVNWA}(x_1, x_2, \cdots, x_n) = \bigoplus_{j=1}^{n} (w_j x_j)
\]

\[
= \left( 1 - \prod_{j=1}^{n} (1 - T_j)^{w_j}, \prod_{j=1}^{n} (I_j)^{w_j}, \prod_{j=1}^{n} (F_j)^{w_j} \right).
\]

**Definition 6.** [41] A pair \((\tilde{F}, A)\) is called a single-valued neutrosophic soft set over \( U \), where \( \tilde{F} \) is a mapping given by \( \tilde{F} : A \rightarrow P(U) \).

In other words, the single-valued neutrosophic soft set is not a kind of set, but a parameterized family of subsets of the set \( U \). For any parameter \( e \in A \), \( \tilde{F}(e) \) may be considered as the set of \( e \)-approximate elements of the single-valued neutrosophic soft set \((\tilde{F}, A)\). Let \( \tilde{F}(e)(x) \) denote the membership value that object \( x \) holds parameter \( e \), then \( \tilde{F}(e) \) can be written as a single-valued neutrosophic set that \( \tilde{F}(e) = \{x/\tilde{F}(e)(x) \mid x \in U\} = \{x/(T(e)(x), I(e)(x), F(e)(x)) \mid x \in U\} \).

**Example 1.** Let \( U = \{x_1, x_2, x_3\} \) and \( A = \{e_1, e_2, e_3\} \). Let \((\tilde{F}, A)\) be a single-valued neutrosophic soft set over \( U \), defined as follows:

\[
\tilde{F}(e_1) = \{x_1/(0.3, 0.4, 0.7), x_2/(0.3, 0.5, 0.6), x_3/(0.4, 0.4, 0.6)\},
\]

\[
\tilde{F}(e_2) = \{x_1/(0.7, 0.4, 0.8), x_2/(0.6, 0.4, 0.6), x_3/(0.3, 0.5, 0.7)\},
\]

\[
\tilde{F}(e_3) = \{x_1/(0.5, 0.4, 0.6), x_2/(0.3, 0.6, 0.7), x_3/(0.3, 0.4, 0.8)\}.
\]

Then, \((\tilde{F}, A)\) is described by the following Table 1.

<table>
<thead>
<tr>
<th></th>
<th>( e_1 )</th>
<th>( e_2 )</th>
<th>( e_3 )</th>
</tr>
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<tbody>
<tr>
<td>( x_1 )</td>
<td>(0.3, 0.4, 0.7)</td>
<td>(0.7, 0.4, 0.8)</td>
<td>(0.5, 0.4, 0.6)</td>
</tr>
<tr>
<td>( x_2 )</td>
<td>(0.3, 0.5, 0.6)</td>
<td>(0.6, 0.4, 0.6)</td>
<td>(0.3, 0.6, 0.7)</td>
</tr>
<tr>
<td>( x_3 )</td>
<td>(0.4, 0.4, 0.6)</td>
<td>(0.3, 0.5, 0.7)</td>
<td>(0.3, 0.4, 0.8)</td>
</tr>
</tbody>
</table>

**Definition 7.** [41] Let \((\tilde{F}, A)\) and \((\tilde{G}, B)\) be two single-valued neutrosophic soft sets over the common universe \( U \). \((F, A)\) is said to be single-valued neutrosophic soft subset of \((G, B)\) if \( A \subseteq B \), \( T_{\tilde{F}}(e)(x) \leq T_{\tilde{G}}(e)(x), I_{\tilde{F}}(e)(x) \leq I_{\tilde{G}}(e)(x), F_{\tilde{F}}(e)(x) \geq F_{\tilde{G}}(e)(x) \) \( \forall e \in A, x \in U \). We denote it by \( (\tilde{F}, A) \subseteq (\tilde{G}, B) \).

### 3. A new single-valued neutrosophic similarity measure

For the existing single-valued neutrosophic similarity measures [21, 22, 42, 43], its similarity result is a fuzzy number, it may lost some original information. In the following, we will propose a new single-valued neutrosophic similarity measure, whose similarity result is still a single-valued neutrosophic number, hence it can be remain more original decision information in some extent.

**Definition 8.** Let \( A_1, A_2 \) and \( A_3 \) be three SVNSs on \( X \). A similarity measure \( S^A : \text{SVNS}(X) \times \text{SVNS}(X) \rightarrow \text{SVNN} \), possessing the following properties:

(1) \( S^A(A_1, A_2) \) is a SVNN;
(2) \( S^A(A_1, A_2) = (1, 0, 0) \) iff \( A_1 = A_2 \);
(3) \( S^A(A_1, A_2) = S^A(A_2, A_1) \);
(4) If \( A_1 \subseteq A_2 \subseteq A_3 \), then \( S^A(A_1, A_2) \supseteq S^A(A_1, A_3) \) and \( S^A(A_2, A_3) \supseteq S^A(A_1, A_3) \).

**Theorem 1.** Let \( A_i \) and \( A_k \) be two SVNSs, then \( S^A(A_i, A_k) \) is a similarity measure.

\[
S^A(A_i, A_k) = \left( \frac{\min\{L(A_i, A_k), M(A_i, A_k), R(A_i, A_k)\}}{\min\{L(A_i, A_k), W(A_i, A_k), R(A_i, A_k)\}}, \frac{1 - \max\{L(A_i, A_k), M(A_i, A_k), R(A_i, A_k)\}}{1 - \max\{L(A_i, A_k), W(A_i, A_k), R(A_i, A_k)\}} \right), \tag{4}
\]

where \( L(A_i, A_k) = \frac{\sum_{j=1}^{n} W_j \min[T_{Tj}, T_{Tj}]}{\sum_{j=1}^{n} W_j \max[T_{Tj}, T_{Tj}]} \).
The (1)-(4) of axiomatic requirements.

Since \(0 \leq L(A_i, A_k) = \frac{\sum_{j=1}^{n} w_j \min[T_{ij}, T_{kj}]}{\sum_{j=1}^{n} w_j \max[T_{ij}, T_{kj}]} \leq 1\),

\[0 \leq M(A_i, A_k) = \frac{\sum_{j=1}^{n} w_j \min[1-I_{ij}, 1-I_{kj}]}{\sum_{j=1}^{n} w_j \max[1-I_{ij}, 1-I_{kj}]} \leq 1,\]

\[0 \leq W(A_i, A_k) = 1 - \frac{\sum_{j=1}^{n} w_j \min[1-I_{ij}, 1-I_{kj}]}{\sum_{j=1}^{n} w_j \max[1-I_{ij}, 1-I_{kj}]} \leq 1,\]

\[0 \leq R(A_i, A_k) = \frac{\sum_{j=1}^{n} w_j \min[1-F_{ij}, 1-F_{kj}]}{\sum_{j=1}^{n} w_j \max[1-F_{ij}, 1-F_{kj}]} \leq 1,\]

therefore,

\[0 \leq \min\{L(A_i, A_k), M(A_i, A_k), R(A_i, A_k)\} \leq 1,\]

\[0 \leq \min\{L(A_i, A_k), W(A_i, A_k), R(A_i, A_k)\} \leq 1,\]

\[0 \leq 1 - \max\{L(A_i, A_k), M(A_i, A_k), R(A_i, A_k)\} \leq 1.\]

Furthermore,

\[0 \leq \min\{L(A_i, A_k), M(A_i, A_k), R(A_i, A_k)\}\]

\[+ \min\{L(A_i, A_k), W(A_i, A_k), R(A_i, A_k)\} + 1 - \max\{L(A_i, A_k), M(A_i, A_k), R(A_i, A_k)\}\]

\[\leq 3.\]

Consequently, \(S^\Delta(A_i, A_k)\) is a SVNN.

(2) \(\exists\) Necessity:

Since \(S^\Delta(A_i, A_k) = (1, 0, 0)\), we have
\n\[
\begin{align*}
\min\{L(A_i, A_k), M(A_i, A_k), R(A_i, A_k)\} &= 1, \\
\min\{L(A_i, A_k), W(A_i, A_k), R(A_i, A_k)\} &= 0, \\
\max\{L(A_i, A_k), M(A_i, A_k), R(A_i, A_k)\} &= 1.
\end{align*}
\]

It means that \(L(A_i, A_k) = M(A_i, A_k) = R(A_i, A_k) = 1, W(A_i, A_k) = 0\).

Furthermore,

\[
\begin{align*}
L(A_i, A_k) &= \frac{\sum_{j=1}^{n} w_j \min[T_{ij}, T_{kj}]}{\sum_{j=1}^{n} w_j \max[T_{ij}, T_{kj}]} = 1, \\
M(A_i, A_k) &= \frac{\sum_{j=1}^{n} w_j \min[1-I_{ij}, 1-I_{kj}]}{\sum_{j=1}^{n} w_j \max[1-I_{ij}, 1-I_{kj}]} = 1, \\
W(A_i, A_k) &= 1 - \frac{\sum_{j=1}^{n} w_j \min[1-I_{ij}, 1-I_{kj}]}{\sum_{j=1}^{n} w_j \max[1-I_{ij}, 1-I_{kj}]} = 0, \\
R(A_i, A_k) &= \frac{\sum_{j=1}^{n} w_j \min[1-F_{ij}, 1-F_{kj}]}{\sum_{j=1}^{n} w_j \max[1-F_{ij}, 1-F_{kj}]} = 1.
\end{align*}
\]

Based on the randomicity of \(w_j\), we can have \(T_{ij} = T_{kj}, I_{ij} = I_{kj}, F_{ij} = F_{kj}\), i.e., \(A_i = A_k\).

(3) It is obvious.

(4) If \(A_1 \subseteq A_2 \subseteq A_3\), then \(\forall j, T_{ij} \leq T_{2j} \leq T_{3j}, I_{1j} \geq I_{2j} \geq I_{3j}\) and \(F_{1j} \geq F_{2j} \geq F_{3j}\).

Hence,

\[
\begin{align*}
L(A_1, A_3) &= \frac{\sum_{j=1}^{n} w_j \min[T_{ij}, T_{3j}]}{\sum_{j=1}^{n} w_j \max[T_{ij}, T_{3j}]} \\
&= \frac{\sum_{j=1}^{n} w_j \min[1-I_{ij}, 1-I_{3j}]}{\sum_{j=1}^{n} w_j \max[1-I_{ij}, 1-I_{3j}]}.
\end{align*}
\]
\[
\begin{align*}
\sum_{j=1}^{n} w_j T_{ij} & \leq \sum_{j=1}^{n} w_j T_{3j} \\
\sum_{j=1}^{n} w_j T_{ij} & = \sum_{j=1}^{n} w_j \min\{T_{ij}, T_{3j}\} = L(A_1, A_2), \\
M(A_1, A_3) & = \frac{\sum_{j=1}^{n} w_j \min\{1 - I_{1j}, 1 - I_{3j}\}}{\sum_{j=1}^{n} w_j \max\{1 - I_{1j}, 1 - I_{3j}\}} \\
W(A_1, A_3) & = 1 - \frac{\sum_{j=1}^{n} w_j (1 - I_{1j})}{\sum_{j=1}^{n} w_j \max\{1 - I_{1j}, 1 - I_{3j}\}} \\
& = 1 - \frac{\sum_{j=1}^{n} w_j (1 - I_{1j})}{\sum_{j=1}^{n} w_j (1 - I_{3j})} \\
& \leq 1 - \frac{\sum_{j=1}^{n} w_j (1 - I_{1j})}{\sum_{j=1}^{n} w_j (1 - I_{2j})} \\
& = 1 - \frac{\sum_{j=1}^{n} w_j \min\{1 - I_{1j}, 1 - I_{2j}\}}{\sum_{j=1}^{n} w_j \max\{1 - I_{1j}, 1 - I_{2j}\}} \\
& = W(A_1, A_2), \\
R(A_1, A_3) & = \frac{\sum_{j=1}^{n} w_j (1 - F_{1j})}{\sum_{j=1}^{n} w_j \max\{1 - F_{1j}, 1 - F_{3j}\}} \\
& \leq \frac{\sum_{j=1}^{n} w_j (1 - F_{3j})}{\sum_{j=1}^{n} w_j (1 - F_{2j})} \\
& = \sum_{j=1}^{n} w_j \min\{1 - F_{1j}, 1 - F_{2j}\} = R(A_1, A_2).
\end{align*}
\]

Furthermore,
\[
\begin{align*}
\min\{L(A_1, A_2), M(A_1, A_2), R(A_1, A_2)\} & \geq \min\{L(A_1, A_3), M(A_1, A_3), R(A_1, A_3)\}, \\
\min\{L(A_1, A_2), W(A_1, A_2), R(A_1, A_2)\} & \geq \min\{L(A_1, A_3), W(A_1, A_3), R(A_1, A_3)\}, \\
1 - \max\{L(A_1, A_2), M(A_1, A_2), R(A_1, A_2)\} & \leq 1 - \max\{L(A_1, A_2), M(A_1, A_2), R(A_1, A_2)\}.
\end{align*}
\]

Consequently, \(S^A(A_1, A_2) \supseteq S^A(A_1, A_3)\). Similarly, \(S^A(A_2, A_3) \supseteq S^A(A_1, A_3)\). This completes the proof.

**Example 2.** [21] Assume that we have the following three SVNSs in a universe of discourse \(X = \{x_1, x_2\}, A \subseteq B \subseteq C, w = \{0.5, 0.5\}:
\[
A = \{< x_1, 0.1, 0.5, 0.6 >, < x_2, 0.2, 0.5, 0.7 >\}, \\
B = \{< x_1, 0.3, 0.4, 0.5 >, < x_2, 0.5, 0.3, 0.4 >\}, \\
C = \{< x_1, 0.6, 0.1, 0.2 >, < x_2, 0.8, 0.1, 0.3 >\}.
\]

By applying the proposed similarity measure,
\[
S^A(A, B) = (0.3750, 0.2308, 0.2308), \\
S^A(B, C) = (0.5714, 0.2778, 0.2778), \\
S^A(A, C) = (0.2143, 0.2143, 0.4444).
\]

Thus, \(S^A(A, C) < S^A(A, B)\) and \(S^A(A, C) < S^A(B, C)\).

### 4. Three algorithms for single-valued neutrosophic soft decision making

#### 4.1. Problem description

Let \(U = \{x_1, x_2, \ldots, x_n\}\) be a finite set of \(m\) alternatives, \(E = \{e_1, e_2, \ldots, e_n\}\) be a set of \(n\)
parameters, and the weight of parameter $e_j$ is $w_j$, $w_j \in [0, 1]$. $\sum_{i=1}^{n} w_i = 1$, $(\tilde{F}, E)$ is single-valued neutrosophic soft set which can be expressed in Table 2.

$\tilde{F}(e_j)(x_i) = (T_{\tilde{F}}(e_j)(x_i), I_{\tilde{F}}(e_j)(x_i), F_{\tilde{F}}(e_j)(x_i))$ represents the possible SVNN of the $i$th alternative $x_i$ satisfying the $j$th parameter $e_j$ which is given by the decision maker.

In the following, we will apply the EDAS, similarity measure and level soft set methods to SVNSS.

4.2. The method of computing the combined weights

We develop a novel method to obtain the weights by combining the subjective elements with the objective ones. This model is different from the existing methods, which can be divided into two tactics: one is the subjective weighting determine methods and the other is the objective weighting methods, which can be computed by grey system theory [50]. The feature of our weighting model can show both the subjective information and the objective information. Hence, combining subjective weights with objective weights, we provide a combined model to determine attribute weights.

4.2.1. Determining the objective weights:

The grey system method

The grey system theory [50] is an excellent tool to deal with small sample and poor information. For a decision maker problem, the alternatives and attributes are generally small which accord with the condition of grey system theory, so we take the method of grey system into consideration.

Theoretically, if an attribute information with respect to other attribute more matches in the average information of the attribute, the attribute contains more information for decision making, the greater the weight. Based on this idea, we propose a grey relational analysis method to determine the attribute weights.

**Definition 9.** Suppose $R = (r_{ij})_{m \times n} (i = 1, 2, \ldots, m; j = 1, 2, \ldots, n)$ be a single-valued neutrosophic matrix. And $S = (s_{ij})_{m \times n} (i = 1, 2, \ldots, m; j = 1, 2, \ldots, n)$ is the score function $s$ (Equation (2)) of $R$. Let $\tilde{s}_i = \frac{1}{n} \sum_{j=1}^{n} s_{ij}$, then the attribute weight $\omega_i$ is defined as follows:

$$\omega_i = 1 - \frac{1}{m} \left( \sum_{j=1}^{m} (\tilde{s}_{ij}) \right)^{\frac{1}{q}},$$

$$n = \frac{1}{m} \sum_{j=1}^{n} \left( \sum_{i=1}^{m} (\tilde{s}_{ij}) \right)^{\frac{1}{q}}.$$

where $\tilde{s}_{ij} = \frac{\min |s_{ij} - \tilde{s}_i| + \xi \max |s_{ij} - \tilde{s}_i|}{|s_{ij} - s_i|}$ is grey mean relational degree, in general, we set $\xi = 0.5$.

In order to improve the effective resolution, this paper uses Euclidean distance instead of Hamming distance, i.e., $q = 2$.

4.2.2. Determining the combined weights:

The non-linear weighted comprehensive method

Suppose that the vector of the subjective weight, given by the decision makers directly, is $w = \{w_1, w_2, \ldots, w_n\}$, where $\sum_{j=1}^{n} w_j = 1$, $0 \leq w_j \leq 1$. The vector of the objective weight, computed by Equation (11) directly, is $\omega = \{w_1, w_2, \ldots, w_n\}$, where $\sum_{j=1}^{n} \omega_j = 1$, $0 \leq \omega_j \leq 1$.

Therefore, the vector of the combined weight $\sigma = \{\sigma_1, \sigma_2, \ldots, \sigma_n\}$ can be defined as follows:

$$\sigma_j = \frac{w_j \times \omega_j}{\sum_{j=1}^{n} w_j \times \omega_j},$$

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

The objective weight and subjective weight are aggregated by non-linear weighted comprehensive method. According to the multiplier effect, the larger the value of the subjective weight and objective weight are, the larger the combined weight is, or vice versa. At the same time, we can obtain that the Equation (6) overcomes the limitation of only considering either subjective or objective factor influence. The advantage of Equation (6) is that the attribute weights and rankings of alternatives can show both the subjective information and the objective information.

4.3. The method of EDAS

In this section, an extended version of the EDAS method is proposed to deal with decision making problems in the single-valued neutrosophic soft environment. Therefore, the concepts and arithmetic
operations of the SVNN are utilized for extending the EDAS method.

Algorithm 1: EDAS

Step 1. Identify the alternatives and parameters, and obtain the single-valued neutrosophic soft set \((\tilde{F}, E)\) which is shown in Table 2.

Step 2. Normalize the single-valued neutrosophic soft set \((\tilde{F}, E)\) into \((\tilde{F}', E)\) by Equation (7).

\[
\tilde{F}'(e_j)(x_i) = \begin{cases} 
T_{\tilde{F}}(e_j)(x_i), & e_j \in B, \\
T_{\tilde{F}}(e_j)(x_i), & e_j \in C, \\
1 - T_{\tilde{F}}(e_j)(x_i), & e_j \in C,
\end{cases}
\]

(7)

where \(B\) is benefit parameter set and \(C\) is cost parameter set.

Step 3. Compute the combined weights by Equation (6).

Step 4. Determine the average solution according to all parameters, shown as follows:

\[
AV = (AV_j)_{1 \times n},
\]

(8)

where

\[
AV_j = \frac{1}{m} \sum_{i=1}^{m} \tilde{F}(e_j)(x_i)
\]

\[
= \frac{1}{m} \left( 1 - \prod_{i=1}^{m} (1 - T_{\tilde{F}}(e_j)(x_i)) \right),
\]

\[
= \left( 1 - \left( \prod_{i=1}^{m} (1 - T_{\tilde{F}}(e_j)(x_i)) \right)^{\frac{1}{m}} \right),
\]

\[
= \left( \prod_{i=1}^{m} I_{\tilde{F}}(e_j)(x_i) \right)^{\frac{1}{m}}, \left( \prod_{i=1}^{m} F_{\tilde{F}}(e_j)(x_i) \right)^{\frac{1}{m}}.
\]

(9)

Step 5. Calculate the positive distance from average (PDA) with \(PDA = (P_{ij})_{m \times n}\) and the negative distance from average (NDA) with \(NDA = (N_{ij})_{m \times n}\) matrices according to the type of parameters, shown as follows:

\[
P_{ij} = \begin{cases} 
\max\{0, s(\tilde{F}(e_j)(x_i)) - s(AV_j)\}, & e_j \in B, \\
\max\{0, s(AV_j) - s(\tilde{F}(e_j)(x_i))\}, & e_j \in C,
\end{cases}
\]

(10)

\[
N_{ij} = \begin{cases} 
\max\{0, s(AV_j) - s(\tilde{F}(e_j)(x_i))\}, & e_j \in B, \\
\max\{0, s(\tilde{F}(e_j)(x_i)) - s(AV_j)\}, & e_j \in C,
\end{cases}
\]

(11)

where \(s(AV_j)\) and \(s(\tilde{F}(e_j)(x_i))\) are score function of \(AV_j\) and \(\tilde{F}(e_j)(x_i)\), respectively.

Step 6. Determine the weighted sum of PDA and NDA for all alternatives, shown as follows:

\[
SP_i = \sum_{j=1}^{n} w_j P_{ij},
\]

(12)

\[
SN_i = \sum_{j=1}^{n} w_j N_{ij}.
\]

(13)

Step 7. Normalize the values of \(SP_i\) and \(SN_i\) for all alternatives, shown as follows:

\[
NSP_i = \frac{SP_i}{\max_i SP_i}
\]

(14)

\[
NSN_i = 1 - \frac{SN_i}{\max_i SN_i}
\]

(15)

Step 8. Calculate the appraisal score \(AS_i(i = 1, 2, \cdots, m)\) for all alternatives, shown as follows:

\[
AS_i = \frac{1}{2}(NSP_i + NSN_i),
\]

(16)

where \(0 \leq AS_i \leq 1\).

Step 9. Rank the alternatives by means of the decreasing values of \(AS_i\). The alternative with the highest \(AS_i\) is the best choice among the candidate alternatives.

4.4. The method of similarity measure

In this section, we introduce a method for the decision making problem by the proposed similarity measure between SVNSs. The concept of ideal point has been applied to help determine the best alternative in the decision process. Although the ideal alternative does not exist in practical problems, it does offer a useful theoretical construct against which to appraise alternatives. Therefore, we define the ideal alternative \(x^*\) as the SVNN \(x_j^* = (T^*, I^*, F^*) = (1, 0, 0)\) for \(\forall j\).
Hence, by applying Equation (3), the proposed similarity measure $S^\Delta$ between an alternative $x_i$ and the ideal alternative $x^*$ represented by the SVNSs is defined by

$$
S^\Delta(x_i, x^*) = \left( \min[L(x_i, x^*), M(x_i, x^*), R(x_i, x^*)], \right.
\min[L(x_i, x^*), W(x_i, x^*), R(x_i, x^*)],
1 - \max[L(x_i, x^*), M(x_i, x^*), R(x_i, x^*)] \right), \tag{17}
$$

where

$$
L(x_i, x^*) = \frac{\sum_{j=1}^{n} \sigma_j \min\{T_{\tilde{F}}(e_j)(x_i), 1\}}{\sum_{j=1}^{n} \sigma_j \max\{T_{\tilde{F}}(e_j)(x_i), 1\}},
$$

$$
M(x_i, x^*) = \frac{\sum_{j=1}^{n} \sigma_j \min\{1 - I_{\tilde{F}}(e_j)(x_i), 1\}}{\sum_{j=1}^{n} \sigma_j \max\{1 - I_{\tilde{F}}(e_j)(x_i), 1\}},
$$

$$
W(x_i, x^*) = 1 - \frac{\sum_{j=1}^{n} \sigma_j \max\{1 - I_{\tilde{F}}(e_j)(x_i), 1\}}{\sum_{j=1}^{n} \sigma_j \max\{1 - I_{\tilde{F}}(e_j)(x_i), 1\}},
$$

$$
R(x_i, x^*) = \frac{\sum_{j=1}^{n} \sigma_j \min\{1 - F_{\tilde{F}}(e_j)(x_i), 1\}}{\sum_{j=1}^{n} \sigma_j \max\{1 - F_{\tilde{F}}(e_j)(x_i), 1\}},
$$

$$
= 1 - \frac{\sum_{j=1}^{n} \sigma_j F_{\tilde{F}}(e_j)(x_i)}{\sum_{j=1}^{n} \sigma_j F_{\tilde{F}}(e_j)(x_i)}.
$$

**Algorithm 2: Similarity measure**

**Steps 1-3.** Similarly to Steps 1-3 in Algorithm 1.

**Step 4.** Calculate the similarity measure $S(x_i, x^*)$ ($i = 1, 2, \ldots, m$) by Equation (17).

**Step 5.** Compute the each alternative of score function $s(S(x_i, x^*))$ by Equation (2).

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

### 4.5. The method of level soft set

We present an adjustable approach to single-valued neutrosophic soft set based decision making problems. This proposal is based on the following novel concept called level soft sets.

**Definition 10.** Let $\Gamma = (\bar{F}, E)$ be a SVNSS over $U$. Let $\lambda : E \rightarrow [0, 1]$ be a function, i.e. $\forall e_j \in E$, $\lambda(e_j) = (r(e_j), k(e_j), t(e_j))$, and $r(e_j), k(e_j), t(e_j) \in [0, 1]$. The level soft set of $\Gamma$ with respect to $\lambda$ is a crisp soft set $L(\Gamma; \lambda) = \langle \bar{F}_\lambda, E \rangle$ defined by $\bar{F}_\lambda(e_j) = L(F(e_j); \lambda(e_j)) = \{x_i \in U | T_{\tilde{F}}(e_j)(x_i) \geq r(e_j), I_{\tilde{F}}(e_j)(x_i) \geq k(e_j), F_{\tilde{F}}(e_j)(x_i) \leq t(e_j)\}$, for all $e_j \in E(j = 1, 2, \ldots, n), x_i \in U(i = 1, 2, \ldots, m)$.

**Remark 1.** In the above definition, the function $\lambda : E \rightarrow [0, 1]^3$ is not restricted to be SVNS, it is only a function, $r(e_j) \in [0, 1]$ can be viewed as a given least threshold (the parameter $e_j$ on the degree of truth-membership), $k(e_j) \in [0, 1]$ can be viewed as a given least threshold (the parameter $e_j$ on the degree of indeterminacy-membership), and $t(e_j) \in [0, 1]$ can be viewed as a given greatest threshold (the parameter $e_j$ on the degree of falsity-membership). Maybe some SVNNs may not strictly follow the Definition 10 ($T_{\tilde{F}}(e_j)(x_i) \geq r(e_j), I_{\tilde{F}}(e_j)(x_i) \geq k(e_j), F_{\tilde{F}}(e_j)(x_i) \leq t(e_j)$), for all $e_j \in E(j = 1, 2, \ldots, n), x_i \in U(i = 1, 2, \ldots, m)$.

We can compute the two SVNSs by score function defined in Equation (2).

**For convenience, we choose mid-level threshold function $mid_{\Gamma}E \rightarrow [0, 1]^3$, i.e.,**

$$
mid_{\Gamma}(e_j) = (r_{mid_{\Gamma}}(e_j), k_{mid_{\Gamma}}(e_j), t_{mid_{\Gamma}}(e_j)) \quad \forall e_j \in E,
$$

where

$$
r_{mid_{\Gamma}}(e_j) = \frac{1}{m} \sum_{i=1}^{m} T_{\tilde{F}}(e_j)(x_i),
$$

$$
k_{mid_{\Gamma}}(e_j) = \frac{1}{m} \sum_{i=1}^{m} I_{\tilde{F}}(e_j)(x_i),
$$

$$
t_{mid_{\Gamma}}(e_j) = \frac{1}{m} \sum_{i=1}^{m} F_{\tilde{F}}(e_j)(x_i).$$
The function mid\( \Gamma \) is called the mid-threshold of \( \Gamma = (\tilde{F}, E) \), the level soft set w.r.t. mid\( \Gamma \), namely \( L(\Gamma; \text{mid}\Gamma) \) is called the mid-level soft set of \( \Gamma \).

**Algorithm 3: Level soft set**

**Steps 1-3.** Similarly to Steps 1-3 in Algorithm 1.

**Step 4.** Compute the mid-level soft set \( L(\Gamma; \text{mid}\Gamma) \).

**Step 5.** Present the mid-level soft set \( L(\Gamma; \text{mid}\Gamma) \) in tabular form and compute the weighted choice value \( c_i \) of \( x_i \) by Equation (18).

\[
c_i = \sum_{j=1}^{n} w_j L(e_j)(x_i).
\]  

**Step 6.** The optimal decision is to select \( x_k \) if \( c_k = \max_{i=1}^{n} c_i \).

5. **A numerical example**

An internet company wants to select a software development project to invest. Assume that there are four software projects: e-commerce development project, game development project, browser development project and web development project. The company selects three parameters to evaluate the four software development projects. Let \( U = \{x_1, x_2, x_3, x_4\} \) be the set of software projects, \( E = \{e_1, e_2, e_3\} \) be the set of parameters, \( e_1 \) stands for economic feasibility, \( e_2 \) stands for technological feasibility, \( e_3 \) stands for staff feasibility. \( e_1 \) and \( e_2 \) are benefit parameters, \( e_3 \) is cost parameter. The weight vector of the parameters is given as \( w = (0.4, 0.1, 0.5)^T \). The decision tabular given by expert is presented in Table 3.

In what follows, we utilize the algorithms proposed above to select software development projects under single-valued neutrosophic soft information.

**Algorithm 1: EDAS**

**Step 1.** Identify the alternatives and parameters, and obtain the single-valued neutrosophic soft set \((\tilde{F}, E)\) which is shown in Table 3.

<table>
<thead>
<tr>
<th>( x_i )</th>
<th>( e_1 )</th>
<th>( e_2 )</th>
<th>( e_3 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( x_1 )</td>
<td>(0.5, 0.4, 0.7)</td>
<td>(0.7, 0.5, 0.1)</td>
<td>(0.6, 0.6, 0.3)</td>
</tr>
<tr>
<td>( x_2 )</td>
<td>(0.6, 0.5, 0.6)</td>
<td>(0.6, 0.2, 0.2)</td>
<td>(0.5, 0.4, 0.4)</td>
</tr>
<tr>
<td>( x_3 )</td>
<td>(0.7, 0.3, 0.5)</td>
<td>(0.7, 0.2, 0.1)</td>
<td>(0.7, 0.5, 0.4)</td>
</tr>
<tr>
<td>( x_4 )</td>
<td>(0.6, 0.4, 0.5)</td>
<td>(0.7, 0.4, 0.2)</td>
<td>(0.5, 0.6, 0.4)</td>
</tr>
</tbody>
</table>

The normalized single-valued neutrosophic soft set \((\tilde{F}, E)\) is shown in Table 4.

<table>
<thead>
<tr>
<th>( x_i )</th>
<th>( e_1 )</th>
<th>( e_2 )</th>
<th>( e_3 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( x_1 )</td>
<td>(0.5, 0.4, 0.7)</td>
<td>(0.7, 0.5, 0.1)</td>
<td>(0.6, 0.4, 0.6)</td>
</tr>
<tr>
<td>( x_2 )</td>
<td>(0.6, 0.5, 0.6)</td>
<td>(0.6, 0.2, 0.2)</td>
<td>(0.4, 0.6, 0.5)</td>
</tr>
<tr>
<td>( x_3 )</td>
<td>(0.7, 0.3, 0.5)</td>
<td>(0.7, 0.2, 0.1)</td>
<td>(0.4, 0.5, 0.7)</td>
</tr>
<tr>
<td>( x_4 )</td>
<td>(0.6, 0.4, 0.5)</td>
<td>(0.7, 0.4, 0.2)</td>
<td>(0.4, 0.4, 0.5)</td>
</tr>
</tbody>
</table>

**Step 2.** Normalize the single-valued neutrosophic soft set \((\tilde{F}, E)\) into \((\tilde{F}', E)\) by Equation (7), which is shown in Table 4.

**Step 3.** Compute the combined weights by Equation (6) as follows:

\[
\omega_1 = 0.4078, \omega_2 = 0.1017, \omega_3 = 0.4905.
\]

**Step 4.** Determine the average solution according to all parameters by Equation (9), shown as follows:

\[
AV_1 = (0.6064, 0.3936, 0.5692),
AV_2 = (0.6776, 0.2991, 0.1414),
AV_3 = (0.5838, 0.5180, 0.3722).
\]

**Step 5.** Calculate the positive distance from average \( PDA = (P_{ij})_{4 \times 3} \) and the negative distance from average \( NDA = (N_{ij})_{4 \times 3} \) matrixes by Equations (10) and (11), shown as follows:

\[
\begin{pmatrix}
0.0000 & 0.0000 & 0.0038 \\
0.0000 & 0.0000 & 0.0038 \\
0.1560 & 0.0728 & 0.0628 \\
0.0343 & 0.0000 & 0.0000
\end{pmatrix},
\begin{pmatrix}
0.1482 & 0.0613 & 0.0000 \\
0.0873 & 0.0166 & 0.0000 \\
0.0000 & 0.0000 & 0.0000 \\
0.0000 & 0.0613 & 0.1143
\end{pmatrix}.
\]

**Step 6.** Determine the weighted sum of \( PDA \) and \( NDA \) for all alternatives by Equations (12) and (13), respectively, shown as follows:

\[
SP_1 = 0.0019, SP_2 = 0.0019,
SP_3 = 0.1019, SP_4 = 0.0140,
NP_1 = 0.0667, NP_2 = 0.0373,
NP_3 = 0.0000, NP_4 = 0.0623.
\]

**Step 7.** Normalize the values of \( SP_i \) and \( SN_i \) for all alternatives by Equations (14) and (15), respectively, shown as follows:
Step 8. Calculate the appraisal score $AS_i (i = 1, 2, 3, 4)$ for all alternatives by Equation (16), shown as follows:

$$AS_1 = -0.0260, \quad AS_2 = 0.2097,$$

$$AS_3 = 1.0000, \quad AS_4 = 0.0687.$$ 

Step 9. Rank the software development projects $x_i$ according to the decreasing values of $AS_i$ as follows:

$$x_3 > x_2 > x_4 > x_1.$$ 

Obviously, amongst them $x_3$ is the best software development project.

Algorithm 2: Similarity measure

Steps 1-3. Similarly to Steps 1-3 in Algorithm 1.

Step 4. Calculate the similarity measure $S(x_i, x^*) (i = 1, 2, 3, 4)$ by Equation (17), shown as follows:

$$S(x_1, x^*) = (0.4223, 0.4102, 0.4101),$$

$$S(x_2, x^*) = (0.4815, 0.5019, 0.4897),$$

$$S(x_3, x^*) = (0.5529, 0.3879, 0.3879),$$

$$S(x_4, x^*) = (0.4695, 0.4000, 0.4000).$$

Step 5. Compute the each alternative of score function $s(S(A_i, A^*))$ by Equation (2), shown as follows:

$$s(S(x_1, x^*)) = 0.533993,$$

$$s(S(x_2, x^*)) = 0.496602,$$

$$s(S(x_3, x^*)) = 0.592335,$$

$$s(S(x_4, x^*)) = 0.556487.$$ 

Step 6. Rank the software development projects by $s(S(x_i, x^*)) (i = 1, 2, 3, 4$) as follows:

$$x_3 > x_4 > x_1 > x_2.$$ 

Obviously, amongst them $x_3$ is the best software development project.

Algorithm 3: Level soft set

Steps 1-3. Similarly to Steps 1-3 in Algorithm 1.

Step 4. Compute the mid-level soft set $L(\Gamma; mid_{\Gamma})$ by Definition 10. $mid_{\Gamma} = \{ < e_1, (0.6, 0.4, 0.575) >,$

< $e_2, (0.675, 0.325, 0.15) >, < e_3, (0.375, 0.475, 0.575) >\}.$

Step 5. Present the mid-level soft set $L(\Gamma; mid_{\Gamma})$ in tabular form and compute the weighted choice value $c_i$ of $x_i$ by Equation (18), which is shown in Table 5.

Step 6. The optimal decision is to select software development project $x_3$.

According to Algorithms 1, 2 and 3, we can conclude that the final decision results are the same, i.e., $x_3$ is the most desirable investment software development project. Hence, the three approaches proposed above are effective and available.

In the following, some comparisons of Algorithm 1, Algorithm 2 and Algorithm 3 are shown.

(1) Comparison of computational complexity

We know that Algorithm 1 will consume more computational complexity than Algorithm 2 and Algorithm 3, especially in Step 4. So if we take the computational complexity into consideration, the Algorithm 2 and Algorithm 3 are given priority to make decision.

(2) Comparison of discrimination

Comparing the results in Algorithm 1, Algorithm 2 with Algorithm 3, we can find that the results of Algorithm 2 are quite close and vary from 0.496602 to 0.592335. These result of decision values cannot clearly distinguish, in other words, the results obtained from Algorithm 2 are not very convincing (or at least not applicable). That is to say, the Algorithm 1 has a clearly distinguish. So if we take the discrimination into consideration, the Algorithm 1 and Algorithm 3 is given priority to make decision.

In order to further verify the practicability of the proposed SVNSS MADM approaches based on the EDAS, similarity measure and level soft set, a comparison study with some existing methods is now conducted in Table 6.

From the above results shown in Table 6, we can know that the optimal alternative of our proposed three methods is in agreement with the existing methods. That is to say, it is effective and feasible.
6. Conclusion and remarks

The major contributions in this paper can be summarized as follows:

(1) We construct a new axiomatic definition of single-valued neutrosophic similarity measure and give a similarity formula. Comparing with the existing literature [21, 22, 42, 43], it can reduce the information miss and remain more original information.

(2) A novel single-valued neutrosophic soft decision making approach based on EDAS is explored, which has not been reported in the existing literature. The approach doesn’t need to calculate the ideal and the nadir solution.

(3) A novel single-valued neutrosophic soft decision making approach based on similarity measure is proposed, which can reduce the information loss and remain more original information.

(4) A novel single-valued neutrosophic soft decision making approach based on level soft set is proposed.

(5) The subjective weighting methods pay much attention to the preference information of the decision maker [19–21, 27], while they neglect the objective information. The objective weighting methods do not take into account the preference of the decision maker, in particular, these methods fail to take into account the risk attitude of the decision maker [22, 24]. The characteristic of our weighting model can reflect both the subjective considerations of the decision maker and the objective information.

In the future, we shall apply more advanced theories [52] into single-valued neutrosophic soft set and solve more decision making problems.

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