LINEAR OPTIMIZATION METHOD ON SINGLE VALUED NEUTROSOPHIC SET AND ITS SENSITIVITY ANALYSIS

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Abstract. Recently, decision making problems has prompted extensive awareness, especially multi-attribute decision-making problem in single valued neutrosophic sets. Given the inherent characteristics of this case, a multi-attribute decision-making problem with a single valued neutrosophic sets (SVN-sets) is explored with both weights and attribute ratings expressed by single valued neutrosophic information. Firstly, some basic concepts concerning SVN-sets are reviewed for the subsequent analysis. Secondly, a linear optimization method of SVN-sets are developed to describe the sensitivity analysis of attribute weights which give changing intervals of attribute weights in which the ranking order of the alternatives is required to remain unchanging. Finally, we presented an illustrative example to show its applicability and effectiveness.

Keywords: Single valued neutrosophic set, linear optimization, sensitivity analysis, multi-attribute decision making.

AMS Subject Classification: 03B52, 03E72

1. INTRODUCTION

Since the increasing lack of knowledge or data about multi attribute decision-making (MADM) problems, decision makers are more and more overwhelmed to make a sound decision. To model the uncertain information some set theory developed such fuzzy set theory [39], intuitionistic fuzzy set theory [1] and neutrosophic sets [31] introduced. The neutrosophic set theory which is characterized by a truth-membership degree, indeterminacy-membership degree and falsity-membership degree to describe the uncertainty and fuzziness more objectively than fuzzy set theory [39] and intuitionistic fuzzy set. Up to now, researches on neutrosophic set theory roughly fall into two groups: theory and application. A lot of work on the neutrosophic set theory has been done such as; on the theory [11, 12, 16, 17, 19, 21, 34] and on application [4, 5, 9, 18, 33, 20]. Also, Nguyen et al. [27] presented an application based on biomedical diagnoses, Liu et al. [25] developed some aggregation operators including score and accuracy functions and Peng et al. [30] proposed outranking approach for single-valued neutrosophic sets.

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§ Manuscript received: April 20, 2018; accepted: March 12, 2019.
TWMS Journal of Applied and Engineering Mathematics Vol.20, No.1 © Işık University, Department of Mathematics, 2020; all rights reserved.
Single valued neutrosophic numbers and their application to multi-criteria decision making problems proposed in [13, 37]. Based on the single valued neutrosophic numbers, various applications have been proposed for fusing neutrosophic number information such triangular neutrosophic numbers [2, 6, 23], trapezoidal neutrosophic numbers [3, 5, 10, 22] and interval trapezoidal neutrosophic numbers [8, 15]. During the last five years, the researchers are paying more attention to this neutrosophic numbers and have effectively applied it to the different situations in applications; on critical path problem [24], on Maclaurin symmetric mean operators [26, 35], on power aggregation operators [36], on neutrosophic single valued neutrosophic numbers and its...
(4) \[ A^\xi = \{x, (T_A(x))^\xi, 1 - (1 - I_A(x))^\xi, 1 - (1 - F_A(x))^\xi) : x \in X \} \]
where \( \xi \in R. \)

For convenience, \[30\] used the notation \( \langle T, I, F \rangle \) instead of \( \langle x, (T_A(x), I_A(x), F_A(x)) \rangle \) for a single valued neutrosophic element of \( x \in X. \)

**Definition 2.4.** \[30\] Let \( X = \{x_1, x_2, \ldots, x_n\} \) be a set of alternatives, \( U = \{o_1, o_2, \ldots, o_m\} \) be the set of attributes. The ratings (or evaluations) of alternatives \( x_j \in X (j = 1, 2, \ldots, n) \) on attributes \( o_i \in U \) are expressed by SVN-number \( A_{ij} = \langle T_{ij}, I_{ij}, F_{ij} \rangle. \)

Then, we present weighted decision making matrix \( [\bar{A}_{ij}]_{m \times n} \) as:

\[
[A_{ij}]_{m \times n} = \begin{pmatrix}
\langle T_{11}, I_{11}, F_{11} \rangle & \langle T_{12}, I_{12}, F_{12} \rangle & \cdots & \langle T_{1n}, I_{1n}, F_{1n} \rangle \\
\langle T_{21}, I_{21}, F_{21} \rangle & \langle T_{22}, I_{22}, F_{22} \rangle & \cdots & \langle T_{2n}, I_{2n}, F_{2n} \rangle \\
\vdots & \vdots & \ddots & \vdots \\
\langle T_{m1}, I_{m1}, F_{m1} \rangle & \langle T_{m2}, I_{m2}, F_{m2} \rangle & \cdots & \langle T_{mn}, I_{mn}, F_{mn} \rangle 
\end{pmatrix}
\]

is called a decision making matrix.

By using \[32\], if we get weighted vector of attribute set \( U \) as

\[
\omega = (\omega_1, \omega_2, \ldots, \omega_m) = (\langle \alpha_1, \beta_1, \gamma_1 \rangle, \langle \alpha_2, \beta_2, \gamma_2 \rangle, \ldots, \langle \alpha_m, \beta_m, \gamma_m \rangle)
\]

then, we present weighted decision making matrix \( [\bar{A}_{ij}]_{m \times n} = \omega [A_{ij}]_{m \times n} \) as;

\[
[A_{ij}]_{m \times n} = \begin{pmatrix}
\langle T_{11}, I_{11}, F_{11} \rangle & \langle T_{12}, I_{12}, F_{12} \rangle & \cdots & \langle T_{1n}, I_{1n}, F_{1n} \rangle \\
\langle T_{21}, I_{21}, F_{21} \rangle & \langle T_{22}, I_{22}, F_{22} \rangle & \cdots & \langle T_{2n}, I_{2n}, F_{2n} \rangle \\
\vdots & \vdots & \ddots & \vdots \\
\langle T_{m1}, I_{m1}, F_{m1} \rangle & \langle T_{m2}, I_{m2}, F_{m2} \rangle & \cdots & \langle T_{mn}, I_{mn}, F_{mn} \rangle 
\end{pmatrix}
\]

where

\[
\langle \bar{T}_{ij}, \bar{I}_{ij}, \bar{F}_{ij} \rangle = \omega_i A_{ij} = \langle \alpha_i, \beta_i, \gamma_i \rangle \langle T_{ij}, I_{ij}, F_{ij} \rangle = \langle \alpha_i T_{ij}, \beta_i I_{ij} + \beta_i F_{ij}, \gamma_i + \gamma_i F_{ij} \rangle
\]

Based on arithmetic average operator of Ye [38] we defined comprehensive evaluation of each alternative \( x_j \in X (j = 1, 2, \ldots, n) \), denoted \( V_j \), is given by;

\[
V_j = \sum_{i=1}^{m} \langle \bar{T}_{ij}, \bar{I}_{ij}, \bar{F}_{ij} \rangle = \langle T_j, I_j, F_j \rangle
\]

Then Liu et al. [25] proposed score and accuracy function to compare two alternatives as;

- (1) score function of \( V_j \) \( (j = 1, 2, \ldots, n) \), denoted \( s(V_j) \), defined as;

\[
s(V_j) = 2 + T_j - F_j - I_j
\]

- (2) accuracy function of \( V_j \) \( (j = 1, 2, \ldots, n) \), denoted \( a(V_j) \), defined as;

\[
a(V_j) = T_j - F_j
\]

and then for \( s, t \in \{1, 2, \ldots, n\}, \)

(a) If \( s(V_s) < s(V_t) \), then \( V_s \) is smaller than \( V_t \), denoted by \( V_s < V_t \)

(b) If \( s(V_s) = s(V_t) \);

(i) If \( a(V_s) < a(V_t) \), then \( V_t \) is smaller than \( V_s \), denoted by \( V_t < V_s \)
(ii) If \( s(V_l) = s(V_s) \), then \( V_l \) and \( V_s \) are the same, denoted by \( V_l = V_s \)

3. Sensitivity analysis

In this section, we present a method is called sensitivity analysis by inspiration from Li [14].

**Definition 3.1. (Sensitivity analysis)** Let \([A_{ij}]_{m \times n}\) be a decision making matrix, \(\omega = (\omega_1, \omega_2, \ldots, \omega_m) = ((\alpha_1, \beta_1, \gamma_1), (\alpha_2, \beta_2, \gamma_2), \ldots, (\alpha_m, \beta_m, \gamma_m))\) be a weighted vector and \(\omega' = ((\alpha_1, \beta_1, \gamma_1), (\alpha_2, \beta_2, \gamma_2), \ldots, (\alpha_k + \Delta\alpha_k, \beta_k + \Delta\beta_k, \gamma_k + \Delta\gamma_k), \ldots, (\alpha_m, \beta_m, \gamma_m))^T\) be a changed weighted vector where \(\Delta\alpha_k, \Delta\beta_k\) and \(\Delta\gamma_k\) are increments of \(\alpha_k, \beta_k\) and \(\gamma_k\), respectively. Then, comprehensive evaluation \(V_j\) of the alternative \(x_j\) is given as:

\[
V_j = \sum_{i=1,i \neq k}^m \omega_i A_{ij} + \omega_k A_{kj} = (x_j, y_j, z_j) \triangleq (\alpha_k T_{kj} - x_j \alpha_k T_{kj}, \beta_k + I_{kj} - \beta k I_{kj}, \gamma_k + F_{kj} - \gamma_k F_{kj})
\]

where

\[
(x_j, y_j, z_j) = \sum_{i=1,i \neq k}^m \omega_i A_{ij}
\]

and

\[
\omega_k A_{kj} = (\alpha_k, \beta_k, \gamma_k) (T_{kj}, I_{kj}, F_{kj}) = (\alpha_k T_{kj}, \beta_k + I_{kj} - \beta k I_{kj}, \gamma_k + F_{kj} - \gamma_k F_{kj})
\]

Therefore, we have:

\[
T_j = x_j + \alpha_k T_{kj} - x_j \alpha_k T_{kj},
I_j = y_j (\beta_k + I_{kj} - \beta k I_{kj})
\]

and

\[
F_j = z_j (\gamma_k + F_{kj} - \gamma_k F_{kj}).
\]

Likewise, the changed comprehensive evaluation \(V'_j\) of the alternative \(x_j\) with the weight change of the attribute \(\omega_k\) can be calculated as follows:

\[
V'_j = (x_j, y_j, z_j) \triangleq (\alpha_k + \Delta \alpha_k) T_{kj}, \beta_k + \Delta \beta_k + I_{kj} - (\beta_k + \Delta \beta_k) I_{kj}, \gamma_k + \Delta \gamma_k + F_{kj} - (\gamma_k + \Delta \gamma_k) F_{kj})
\]

where

\[
\omega_k A_{kj} = (\alpha_k + \Delta \alpha_k, \beta_k + \Delta \beta_k, \gamma_k + \Delta \gamma_k) (T_{kj}, I_{kj}, F_{kj}) = ((\alpha_k + \Delta \alpha_k) T_{kj}, \beta_k + \Delta \beta_k + I_{kj} - (\beta_k + \Delta \beta_k) I_{kj}, \gamma_k + \Delta \gamma_k + F_{kj} - (\gamma_k + \Delta \gamma_k) F_{kj})
\]

Similarly, the changed comprehensive evaluations \(V'_s\) and \(V'_t\) of the alternatives \(x_s\) and \(x_t\) with the weight change of the attribute \(\omega_k\) is given as:

\[
V'_s = (x_s, y_s, z_s) \triangleq ((\alpha_k + \Delta \alpha_k) T_{ks}, \beta_k + \Delta \beta_k + I_{ks} - (\beta_k + \Delta \beta_k) I_{ks}, \gamma_k + \Delta \gamma_k + F_{ks} - (\gamma_k + \Delta \gamma_k) F_{ks})
\]

and

\[
V'_t = (x_t, y_t, z_t) \triangleq ((\alpha_k + \Delta \alpha_k) T_{kt}, \beta_k + \Delta \beta_k + I_{kt} - (\beta_k + \Delta \beta_k) I_{kt}, \gamma_k + \Delta \gamma_k + F_{kt} - (\gamma_k + \Delta \gamma_k) F_{kt})
\]
respectively, where

\[ T_s = x_s + \alpha_k T_{ks} - x_s \alpha_k T_{ks}, \]
\[ I_s = y_s(\beta_k + I_{ks} - \beta_k I_{ks}), \]
\[ F_s = z_s(\gamma_k + F_{ks} - \gamma_k F_{ks}), \]
\[ T_t = x_t + \alpha_k T_{kt} - x_t \alpha_k T_{kt}, \]
\[ I_t = y_t(\beta_k + I_{kt} - \beta_k I_{kt}) \]
and
\[ F_t = z_t(\gamma_k + F_{kt} - \gamma_k F_{kt}). \]

Then, we can calculate the scores of \( V_j', V_s', \) and \( V_t' \) as follows:

\[ s(V_j') = 2 + T_j - I_j - F_j + \Delta \alpha_k T_{kj}(1 - x_j) - \Delta \beta_k y_j(1 - I_{kj}) - \Delta \gamma_k z_j(1 - F_{kj}) \]
\[ s(V_s') = 2 + T_s - I_s - F_s + \Delta \alpha_k T_{ks}(1 - x_s) - \Delta \beta_k y_s(1 - I_{ks}) - \Delta \gamma_k z_s(1 - F_{ks}) \]
\[ s(V_t') = 2 + T_t - I_t - F_t + \Delta \alpha_k T_{kt}(1 - x_t) - \Delta \beta_k y_t(1 - I_{kt}) - \Delta \gamma_k z_t(1 - F_{kt}) \]

Also, we can obtain the accuracies of \( V_j', V_s', \) and \( V_t' \) as follows:

\[ a(V_j') = T_j - F_j + \Delta \alpha_k T_{kj}(1 - x_j) - \Delta \gamma_k z_j(1 - F_{kj}) \]
\[ a(V_s') = T_s - F_s + \Delta \alpha_k T_{ks}(1 - x_s) - \Delta \gamma_k z_s(1 - F_{ks}) \]
\[ a(V_t') = T_t - F_t + \Delta \alpha_k T_{kt}(1 - x_t) - \Delta \gamma_k z_t(1 - F_{kt}) \]

Suppose that the ranking the alternatives \( x_j, x_s \) and \( x_t \) is \( x_j > x_s > x_t \). When the weight \( \omega_t \) of the attribute \( a_k \) is changed to \( \omega_t' \), if the ranking order of the alternatives \( x_j, x_s \) and \( x_t \) are required to remain unchanging, then \( V_j', V_s', \) and \( V_t' \) should satisfy either

1. \( s(V_j') > s(V_s') \) and \( s(V_s') > s(V_t') \)
2. \( s(V_j') = s(V_s'), s(V_s') = s(V_t'), a(V_j') > a(V_s'), a(V_s') > a(V_t') \)

Therefore, we have following inequalities:

1. \( s(V_j') > s(V_s') \)
   \( s(V_s') > s(V_t') \)
   \[ 0 \leq \alpha_k + \Delta \alpha_k + \beta_k + \Delta \beta_k + \gamma_k + \Delta \gamma_k \leq 3, \]
   \[ 0 \leq \alpha_k + \Delta \alpha_k \leq 1 \]
   \[ 0 \leq \beta_k + \Delta \beta_k \leq 1 \]
   \[ 0 \leq \gamma_k + \Delta \gamma_k \leq 1 \]

2. \( s(V_j') = s(V_s') \)
   \( s(V_s') = s(V_t') \)
   \( a(V_j') > a(V_s') \)
   \( a(V_s') > a(V_t') \)
   \[ 0 \leq \alpha_k + \Delta \alpha_k + \beta_k + \Delta \beta_k + \gamma_k + \Delta \gamma_k \leq 3, \]
   \[ 0 \leq \alpha_k + \Delta \alpha_k \leq 1 \]
   \[ 0 \leq \beta_k + \Delta \beta_k \leq 1 \]
   \[ 0 \leq \gamma_k + \Delta \gamma_k \leq 1 \]

and

Solving either 1. or 2., we can obtain the changing ranges \( \Delta \alpha_k, \Delta \beta_k \) and \( \Delta \gamma_k \) of the weight \( \omega_k \) of the attribute \( a_k \). Namely, if the weight \( \omega_k \) takes any value between \( \langle \alpha_k, \beta_k, \gamma_k \rangle \); and \( \langle \alpha_k + \Delta \alpha_k, \beta_k + \Delta \beta_k, \gamma_k + \Delta \gamma_k \rangle \), then, the ranking order of the alternatives still remains unchanging.
4. A Linear Optimization Method based on sensitivity analysis of SVN-sets

In this section, we give a method, which is called linear weighted averaging method, for sensitivity analysis of SVN-weights of the attributes;

Let $X = \{x_1, x_2, ..., x_n\}$ be a set of alternatives, $O = \{o_1, o_2, ..., o_m\}$ be the set of attributes.

**Algorithm:**

*Step 1:* Input decision making matrix $[A_{ij}]_{m \times n}$;

*Step 2:* Determine the weighted decision making matrix $[A_{ij}]_{m \times n}$;

*Step 3:* Find the weighted decision making matrix $[A_{ij}]_{m \times n}$;

*Step 4:* Calculate $V_j = \sum_{i=1}^{m} (T_{ij}, I_{ij}, F_{ij}) = (T_j, I_j, F_j)$ of the alternatives $x_j \in X(j = 1, 2, ..., n)$;

*Step 5:* Rank the alternatives by using score and accuracy functions based $V_j(j = 1, 2, ..., n)$ according to Definition 2.4;

*Step 6:* Compute the sensitivity analysis of weights of the attributes in the linear optimization method based Definition 3.1;

5. Application

Assume that $X = \{x_1, x_2, x_3\}$ be a set of alternatives and $O = \{o_1, o_2, o_3\}$ be the set of attributes. Then, a decision maker wants to select the best alternative considering three attribute. Therefore decision progress is given as:

*Step 1:* Decision making matrix $[A_{ij}]_{3 \times 3}$ entered as:

$$[A_{ij}]_{3 \times 3} = \begin{pmatrix}
0.7, 0.1, 0.8 & 0.7, 0.6, 0.8 & 0.1, 0.4, 0.7 \\
0.5, 0.2, 0.8 & 0.4, 0.2, 0.3 & 0.2, 0.1, 0.9 \\
0.1, 0.1, 0.6 & 0.8, 0.5, 0.4 & 0.6, 0.3, 0.7
\end{pmatrix}$$

*Step 2:* The weighted vector is determined as

$$\omega = (0.2, 0.9, 0.8) \times (0.8, 0.4, 0.9) \times (0.7, 0.6, 0.3)$$

*Step 3:* Weighted decision making matrix $[A_{ij}]_{3 \times 3}$ found as:

$$[A_{ij}]_{3 \times 3} = \begin{pmatrix}
0.14, 0.91, 0.96 & 0.14, 0.96, 0.96 & 0.02, 0.94, 0.94 \\
0.40, 0.52, 0.98 & 0.32, 0.52, 0.93, & 0.16, 0.46, 0.99 \\
0.07, 0.64, 0.72 & 0.56, 0.80, 0.58 & 0.42, 0.72, 0.79
\end{pmatrix}$$

*Step 4:* The $V_j$ of the alternatives $x_j \in X(j = 1, 2, ..., n)$ calculated as:

$$V_1 = (1 - (1 - 0.14)(1 - 0.40)(1 - 0.07), 0.91 \times 0.52 \times 0.64, 0.96 \times 0.98 \times 0.72)$$
$$= (0.52012, 0.30285, 0.67738)$$

$$V_2 = (1 - (1 - 0.14)(1 - 0.32)(1 - 0.56), 0.96 \times 0.52 \times 0.80, 0.96 \times 0.93 \times 0.58)$$
$$= (0.74269, 0.39936, 0.51782)$$

and

$$V_3 = (1 - (1 - 0.02)(1 - 0.16)(1 - 0.42), 0.94 \times 0.46 \times 0.72, 0.94 \times 0.99 \times 0.79)$$
$$= (0.52254, 0.31133, 0.73517)$$

respectively.
Step 5: The scores of $V_j (j = 1, 2, 3)$ are calculated as:

$$s(V_1) = 1.53990$$
$$s(V_2) = 1.82550$$

and

$$s(V_3) = 1.47604$$

respectively. Then we have get $x_2 > x_1 > x_3$.

Step 6: We computed the sensitivity analysis of weight $\omega_2$ of the attribute $o_2$ in the linear optimization method based Definition 3.1 as;

(Similarly, the analysis can be made for $\omega_1$ and $\omega_3$)

Firstly, we assume that only weight $\omega_2 = \{\alpha_2, \beta_2, \gamma_2\}$ of the attribute $o_2$ is changed to the weight $\bar{\omega}_2 = \{\alpha_2 + \Delta \alpha_2, \beta_2 + \Delta \beta_2, \gamma_2 + \Delta \gamma_2\}$ and the weights of other attributes $\alpha_i (i = 1, 3)$ remain the same as the original weights $\omega_1$ and $\omega_3$.

Then, we have the systems of inequalities as follows:

$$s(V'_2) > s(V'_1)$$
$$s(V'_1) > s(V'_3)$$
$$0 \leq \alpha_2 + \Delta \alpha_2 + \beta_2 + \Delta \beta_2 + \gamma_2 + \Delta \gamma_2 \leq 3,$$
$$0 \leq 0.8 + \Delta \alpha_2 \leq 1$$
$$0 \leq 0.4 + \Delta \beta_2 \leq 1$$
$$0 \leq 0.9 + \Delta \gamma_2 \leq 1$$

where

$$s(V'_1) = 2 + T_1 - I_1 - F_1 + \Delta \alpha_2 T_21(1 - x_1) - \Delta \beta_2 y_1(1 - I_21) - \Delta \gamma_2 z_1(1 - F_21)$$
$$= 1.35176 + 0.31992\Delta \alpha_2 - 0.27955\Delta \beta_2 - 0.01382\Delta \gamma_2$$

$$s(V'_2) = 2 + T_2 - I_2 - F_2 + \Delta \alpha_2 T_22(1 - x_2) - \Delta \beta_2 y_2(1 - I_22) - \Delta \gamma_2 z_2(1 - F_22)$$
$$= 1.38793 + 0.12109\Delta \alpha_2 - 0.36864\Delta \beta_2 - 0.03898\Delta \gamma_2$$

$$s(V'_3) = 2 + T_3 - I_3 - F_3 + \Delta \alpha_2 T_23(1 - x_3) - \Delta \beta_2 y_3(1 - I_23) - \Delta \gamma_2 z_3(1 - F_23)$$
$$= 1.30498 + 0.09094\Delta \alpha_2 - 0.36547\Delta \beta_2 - 0.00743\Delta \gamma_2$$

$$T_1 = 0.45614$$
$$I_1 = 0.41467$$
$$F_1 = 0.68982$$
$$T_2 = 0.71847$$
$$I_2 = 0.46694$$
$$F_2 = 0.86360$$
$$T_3 = 0.50436$$
$$I_3 = 0.45752$$
$$F_3 = 0.74186$$

which can be simplified into the system of inequalities as follows:

$$0.03628 - 0.19883\Delta \alpha_2 - 0.08909\Delta \beta_2 - 0.02515\Delta \gamma_2 > 0$$
$$0.04667 + 0.22898\Delta \alpha_2 + 0.08592\Delta \beta_2 - 0.00640\Delta \gamma_2 > 0$$
$$-0.8 \leq \Delta \alpha_2 \leq 0.2$$
$$-0.4 \leq \Delta \beta_2 \leq 0.6$$
$$-0.9 \leq \Delta \gamma_2 \leq 0.1$$

Some solutions of the system is given by Fig. 1.

Likewise, we assume that only weight $\omega_1 = \{\alpha_1, \beta_1, \gamma_1\}$ of the attribute $o_1$ is changed to the weight $\bar{\omega}_1 = \{\alpha_1 + \Delta \alpha_1, \beta_1 + \Delta \beta_1, \gamma_1 + \Delta \gamma_1\}$ and the weights of other attributes
Figure 1. Some solutions of the system

\[ o_i (i = 2, 3) \] remain the same as the original weights or that only weight \( \omega_3 = \langle \alpha_3, \beta_3, \gamma_3 \rangle \) of the attribute \( o_3 \) is changed to the weight \( \bar{\omega}_3 = \langle \alpha_3 + \Delta \alpha_3, \beta_3 + \Delta \beta_3, \gamma_3 + \Delta \gamma_3 \rangle \) and the weights of other attributes \( o_i (i = 1, 2) \) remain the same as the original weights, then the solutions can easily be made in a similar way for \( o_1 \) and \( o_3 \).

6. Conclusion

In this study, we proposed a linear optimization method of SVN-sets to describe the sensitivity analysis of attribute weights. Also we an application which show its applicability and effectiveness. Finally, we applied our proposed method to a multi-attribute decision-making problem to demonstrate its feasibility and stability in solution. Since our paper still has some limitations, in future studies we will study on different methods by combining other objective methods for determining criteria weights in neutrosophic sets.

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