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Aralık Nötrosofik Kümeler Arasında Mesafe Tabanlı Benzerlik Ölçüsü ve Çok Kriterli Karar Verme Metodu

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ÖZET: Bu makalede, Hamming ve Öklid uzaklığa dayanan ağırlıklı benzerlik ölçüsü, aralık nötrosofik kümelere genişletilmiştir. Bu ölçü daha önce tek değerli nötrosofik kümeler için kullanılmıştır. Daha sonra kriter ağırlıkları bilinen çok kriterli bir karar verme metodu oluşturulmuştur. Problemde, her bir alternatifin kriterlere göre değerleri aralık nötrosofik sayılarla verilmiştir. Son olarak ideal alternatif ile her bir alternatif arasında ağırlıklı benzerlik ölçüsü kullanılarak alternatifler sıralanmış ve en iyi alternatif belirlenmiştir.

Anahtar Kelimeler: Hamming ve Öklid uzaklık, benzerlik ölçüsü, aralık nötrosofik küme, çok kriterli karar verme

Distance-Based Similarity Measure Between Interval Neutrosophic Sets and Multi Criteria Decision Making Method

ABSTRACT: In this paper, the weighted similarity measure based on Hamming and Euclidean distances is extended to interval neutrosophic sets. It has been previously used for single valued neutrosophic sets. Then a multicriteria decision-making (MCDM) method is established, in which the criterion weights are known. In the problem the values of each alternative corresponding to the criteria are given with interval neutrosophic numbers. Finally, alternatives are ranked by using the weighted similarity measure between the ideal alternative and each alternative, and the best one is determined.

Keywords: Hamming and Euclidean distances, similarity measure, interval neutrosophic set, multi criteria decision-making.

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INTRODUCTION

With the proposal of the fuzzy set (FS) theory (Zadeh, 1965), the subject is not based on finding a wide application area but based on the development of the intuitionistic fuzzy set (IFS) (Atanassov,1986), the interval valued intuitionistic fuzzy set (IVIFS) (Atanassov ve Gargov 1989), the neutrosophic set (NS) (Smarandache, 1999), the interval neutrosophic set (INS) (Wang et al., 2005) and single valued neutrosophic set (SVNS)) (Wang et al., 2010). In NS indeterminacy is clearly stated and the set is represented by the truth-membership function $T_A(x)$, an indeterminacy-membership function $I_A(x)$ and a falsity-membership function $F_A(x)$, which are completely independent of each other. This information is important as it carries more information on modeling uncertainties. SVNS and INS are subsets of the NS and INS represents the uncertain, incomplete and inconsistent information better that exists in the real world.

MCDM problems have been researched by many authors and accordingly different methods have been developed to obtain the solution (Broumi et al., 2014a; Broumi et al., 2014b; Broumi et al., 2014c; Broumi et al., 2015; Chi et al., 2013;Deli, 2015; Deli et al.,2018; Ye 2013; Peng et al., 2015; Şahin, 2015; Küçük and Şahin, 2018; Şahin and Küçük, 2018). Hamming, Euclidean distances were defined and a similarity measure was proposed for INSs (Ye, 2014a).

The comparisons and operations between the interval neutrosophic numbers (INNs) and the average operators are included in the study (Zhang et al., 2014). (Ye, 2014b) extended the similarity measure between interval fuzzy values (IFVs) defined by (Xu and Yager,2009) to SVNSs and also defined the weighted similarity measure for SVNSs.

In this study after defining the NS (Smarandache, 1999), SVNS (Wang ve ark., 2010) and similarity measures for this set (Ye, 2014 b), Hamming and Euclidean distances definitions are given. Then the distance-based similarity measure defined by (Ye, 2014b) is extended to INSs and some properties of them are presented. Later a MCDM method based on similarity measure has been developed for these sets and the developed method is implemented to a decision making (DM) problem and the alternatives are ranked with the help of the ideal alternative. Finally, a brief summary of the work is presented.

MATERIALS AND METHODS

Some Concepts of SVNSs

Definition 1. (Smarandache, 1999) Let X be a space of points with generic elements in X denoted by x. A neutrosophic set (NS) A in X is characterized by a truth-membership function $T_A(x)$, an indeterminacy-membership function $I_A(x)$ and a falsity-membership function $F_A(x)$. The functions $T_A(x), I_A(x)$ and $F_A(x)$ are real standard/nonstandard subset of $]^-0,1^+[$, that is $T_A: X \to]^-0,1^+[$, $I_A: X \to]^-0,1^+[$ and $F_A: X \to]^-0,1^+[$ such that $^-0 \leq \sup T_A(x) + \sup I_A(x) + \sup F_A(x) \leq 3^+$.

Definition 2. (Wang et al., 2010) Let X be a space of points with generic elements in X denoted by x. A SVNS A in X is characterized by a truth-membership function $T_A(x)$, an indeterminacy-membership function $I_A(x)$ and a falsity-membership function $F_A(x)$. For each point x in X, there are $T_A(x), I_A(x), F_A(x) \in [0,1]$, and $0 \leq T_A(x) + I_A(x) + F_A(x) \leq 3$. Therefore, a SVNS A can be represented by

$$A = \{\langle x, T_A(x), I_A(x), F_A(x)\rangle : x \in X\},$$

A single valued neutrosophic number (SVNN) is denoted by $a = (T_a, I_a, F_a)$.

Let $A = \{\langle x, T_A(x), I_A(x), F_A(x)\rangle : x \in X\}$ be a SVNS. Then the complement of A is defined as follows:

$$A^c = \{\langle x, F_A(x), 1 - I_A(x), T_A(x)\rangle : x \in X\}.$$

Definition 3. (Ye, 2014b) Let $\alpha_1 = (T_1, I_1, F_1)$ and $\alpha_2 = (T_2, I_2, F_2)$ be SVNNs. Normalized Hamming distance between α_1 and α_2 is defined as follows:

$$d(\alpha_1, \alpha_2) = \frac{1}{3}(|T_1 - T_2| + |I_1 - I_2| + |F_1 - F_2|).$$

Definition 4. (Ye, 2014b) Let $\alpha_1 = (T_1, I_1, F_1)$ and $\alpha_2 = (T_2, I_2, F_2)$ be two SVNNs. Similarity measure between α_1 and α_2 is defined as:

$$S(\alpha_1, \alpha_2) = \begin{cases} 0.5, & \text{if } \alpha = \alpha_2 = \overline{\alpha_2} \\ \dfrac{d(\alpha_1, \overline{\alpha_2})}{d(\alpha_1, \alpha_2) + d(\alpha_1, \overline{\alpha_2})}, & \text{otherwise} \end{cases}$$

where $\overline{\alpha_2} = (F_2, 1 - I_2, T_2)$ is the complement of α_2. $S(\alpha_1, \alpha_2)$ satisfies the following properties:

1) $0 \leq S(\alpha_1, \alpha_2) \leq 1$;
2) $S(\alpha_1, \alpha_2) = 1 \Leftrightarrow \alpha_1 = \alpha_2$;
3) $S(\alpha_1, \alpha_2) = S(\alpha_2, \alpha_1)$;
4) If $d(\alpha_1, \alpha_2) = d(\alpha_1, \overline{\alpha_2})$, then $S(\alpha_1, \alpha_2) = 0.5$;
5) If $\alpha_1 = \overline{\alpha_2}$, then $S(\alpha_1, \alpha_2) = 0$.

Definition 5. (Ye, 2014b) Let $\mathrm{A}_1 = \{\alpha_1, \alpha_2, \dots, \alpha_n\}$ and $\mathrm{A}_2 = \{\beta_1, \beta_2, \dots, \beta_n\}$ be SVNSs. Similarity measure between A_1, A_2 is defined as:

$$S(\mathrm{A}_1, \mathrm{A}_2) = \frac{1}{n}\sum_{j=1}^{n} \frac{d(\alpha_j, \overline{\beta_j})}{d(\alpha_j, \beta_j) + d(\alpha_j, \overline{\beta_j})}$$

where α_j and β_j $(j = 1,2, \dots, n)$ are SVNNs. For every j, if $\alpha_j = \beta_j = \overline{\beta_j}$, then

$$\frac{d(\alpha_j, \overline{\beta_j})}{d(\alpha_j, \beta_j) + d(\alpha_j, \overline{\beta_j})} = 0.5.$$

$S(\mathrm{A}_1, \mathrm{A}_2)$ satisfies following properties:

1) $0 \leq S(\mathrm{A}_1, \mathrm{A}_2) \leq 1$;
2) $S(\mathrm{A}_1, \mathrm{A}_2) = 1 \Leftrightarrow \alpha_1 = \alpha_2$;
3) $S(\mathrm{A}_1, \mathrm{A}_2) = S(\mathrm{A}_2, \mathrm{A}_1)$;
4) If $d(\alpha_j, \beta_j) = d(\alpha_j, \overline{\beta_j})$, then $S(\mathrm{A}_1, \mathrm{A}_2) = 0.5$ $(j = 1,2, \dots, n)$.
5) If $\alpha_j = \overline{\beta_j}$, then $S(\mathrm{A}_1, \mathrm{A}_2) = 0$ $(j = 1,2, \dots, n)$.

If the weight w_j $\left(w_j \in [0,1], \sum_{j=1}^{n} w_j = 1\right)$ for each element α_j or β_j $(j = 1,2, \dots, n)$, then the weighted similarity measure between $\mathrm{A}_1, \mathrm{A}_2$ is defined as (Ye, 2014b):

$$S_w(A_1, A_2) = \sum_{j=1}^{n} w_j \frac{d(\alpha_j, \overline{\beta_j})}{d(\alpha_j, \beta_j) + d(\alpha_j, \overline{\beta_j})} \quad (1)$$

(1) satisfies the properties (1-5)

Some Concepts of INSs

Definition 6. (Wang et al., 2005) Let X be a discourse universe and $x \in X$. An interval neutrosophic set A in X is defined as follows:

$$A = \{\langle x, [T^L(x), T^U(x)], [I^L(x), I^U(x)], [F^L(x), F^U(x)]\rangle : x \in X\},$$

where $T_A(x) = [T^L(x), T^U(x)], I_A(x) = [I^L(x), I^U(x)], F_A(x) = [F^L(x), F^U(x)] \subseteq [0,1]$ are truth-membership function, indeterminacy-membership function and falsity-membership functions, respectively and for every $x \in X$, $0 \leq T^U(x) + I^U(x) + F^U(x) \leq 3$.

For the rest of the paper $\alpha = ([T^L, T^U], [I^L, I^U], [F^L, F^U])$ represents interval neutrosophic number (INN).

RESULTS AND DISCUSSION

Similarity Measure Between INS

In this section, the similarity measure defined in (1) is extended to INS.

Definition 7. (Ye 2014 a) Let $\alpha = ([T_1^L, T_1^U], [I_1^L, I_1^U], [F_1^L, F_1^U])$ and

$\beta = ([T_2^L, T_2^U], [I_2^L, I_2^U], [F_2^L, F_2^U])$ be two INNs;

1) Hamming distance between α and β is defined as:

$$D_H(\alpha, \beta) = \frac{1}{6}(|T_1^L - T_2^L| + |T_1^U - T_2^U| + |I_1^L - I_2^L| + |I_1^U - I_2^U| + |F_1^L - F_2^L| + |F_1^U - F_2^U|) \quad (2)$$

2) Euclidean distance between α and β is defined as:

$$D_E(\alpha, \beta) = \sqrt{\frac{1}{6}((T_1^L - T_2^L)^2 + (T_1^U - T_2^U)^2 + (I_1^L - I_2^L)^2 + (I_1^U - I_2^U)^2 + (F_1^L - F_2^L)^2 + (F_1^U - F_2^U)^2)} \quad (3)$$

Definition 8. (Wang et al., 2005) The complement of an interval neutrosophic set A is denoted by $\bar{A}$ and it is defined by

$$\bar{A} = [F^L(x), F^U(x)], [1 - I^U(x), 1 - I^L(x),], [T^L(x), T^U(x)]$$

for all x in X.

Definition 9. Let $\alpha = ([T_1^L, T_1^U], [I_1^L, I_1^U], [F_1^L, F_1^U]), \beta = ([T_2^L, T_2^U], [I_2^L, I_2^U], [F_2^L, F_2^U])$ be two INNs and $\bar{\beta} = ([F_2^L, F_2^U], [1 - I_2^U, 1 - I_2^L,], [F_2^L, F_2^U])$ is the complement of β.

The similarity measure between α and β is defined as follows:

$$s(\alpha, \beta) = \begin{cases} 0.5, & \text{if } \alpha = \beta = \bar{\beta}, \\ \frac{D(\alpha, \bar{\beta})}{D(\alpha, \beta) + D(\alpha, \bar{\beta})}, & otherwise \end{cases} \quad (4)$$

where D is the distance given in Definition 7.

Theorem 1: $s(\alpha,\beta)$ satisfies following properties:

1) $0 \le s(\alpha,\beta) \le 1$;
2) $s(\alpha,\beta) = 1 \Leftrightarrow \alpha = \beta$;
3) $s(\alpha,\beta) = s(\beta,\alpha)$;
4) If $D(\alpha,\beta) = D(\alpha,\bar{\beta})$, then $s(\alpha,\beta) = 0.5$.
5) If $\alpha = \bar{\beta}$, then $s(\alpha,\beta) = 0$.

Proof.

1. Since $0 \le D(\alpha,\bar{\beta}) \le 1$ and $0 \le D(\alpha,\beta) \le 1$, it is obtained that $0 \le \frac{D(\alpha,\bar{\beta})}{D(\alpha,\beta)+D(\alpha,\bar{\beta})} \le 1$. Hence, $0 \le s(\alpha,\beta) \le 1$.

2. Let $s(\alpha,\beta) = 1$. Then $\frac{D(\alpha,\bar{\beta})}{D(\alpha,\beta)+D(\alpha,\bar{\beta})} = 1$. So it is obvious that $D(\alpha,\beta) = 0$. This equality is provided when $\alpha = \beta$.

When $\alpha = \beta$, it is obtained that $D(\alpha,\beta) = 0$. So we can write $\frac{D(\alpha,\bar{\beta})}{D(\alpha,\beta)+D(\alpha,\bar{\beta})} = 1$ and $s(\alpha,\beta) = 1$.

3. To prove $s(\alpha,\beta) = s(\beta,\alpha)$, it is sufficient to show that $D(\alpha,\bar{\beta}) = D(\beta,\bar{\alpha})$ is provided.

$$D(\alpha,\bar{\beta}) = \frac{1}{6}\left(|T_1^L - F_2^L| + |T_1^U - F_2^U| + |I_1^L - (1 - I_2^U)| + |I_1^U - (1 - I_2^L)| + |F_1^L - T_2^L| + |F_1^U - T_2^U|\right)$$
$$= \frac{1}{6}\left(|T_2^L - F_1^L| + |T_2^U - F_1^U| + |I_2^L - (1 - I_1^U)| + |I_2^U - (1 - I_1^L)| + |F_2^L - T_1^L| + |F_2^U - T_1^U|\right)$$
$$= D(\beta,\bar{\alpha})$$

Theorem can be proven for Euclidean distance in the same way.

4. When $D(\alpha,\beta) = D(\alpha,\bar{\beta})$, it is obvious that $\beta = \bar{\beta}$.

$$\frac{D(\alpha,\bar{\beta})}{D(\alpha,\beta)+D(\alpha,\bar{\beta})} = \frac{D(\alpha,\bar{\beta})}{D(\alpha,\bar{\beta})+D(\alpha,\bar{\beta})} = 0.5$$

so we get

$$s(\alpha,\beta) = \begin{cases} 0.5, & \text{if } \alpha = \beta = \bar{\beta}, \\ 0.5, & \mathit{otherwise} \end{cases}$$

5. If $\alpha = \bar{\beta}$, then $D(\alpha,\bar{\beta}) = 0$. Hence we get $s(\alpha,\beta) = 0$.

Definition 10. Let $A_1 = \{\alpha_1, \alpha_2, \dots, \alpha_n\}$, $A_2 = \{\beta_1, \beta_2, \dots, \beta_n\}$ be two INSs. The similarity measure between A_1, A_2 is defined as follows:

$$s(A_1, A_2) = \frac{1}{n}\sum_{j=1}^{n} \frac{D(\alpha_j,\overline{\beta_j})}{D(\alpha_j,\beta_j)+D(\alpha_j,\overline{\beta_j})} \qquad (5)$$

where α_j ve β_j are INNs. If $\alpha_j = \beta_j = \overline{\beta_j}$, then

$$\frac{D(\alpha_j,\overline{\beta_j})}{D(\alpha_j,\beta_j)+D(\alpha_j,\overline{\beta_j})} = 0.5.$$

Theorem 2: $s(\mathrm{A}_1, \mathrm{A}_2)$ satisfies the following properties:

1) $0 \leq s(\mathrm{A}_1, \mathrm{A}_2) \leq 1$;
2) $s(\mathrm{A}_1, \mathrm{A}_2) = 1 \Leftrightarrow \mathrm{A}_1 = \mathrm{A}_2$;
3) $s(\mathrm{A}_1, \mathrm{A}_2) = s(\mathrm{A}_2, \mathrm{A}_1)$;
4) If $D(\alpha_j, \beta_j) = D(\alpha_j, \overline{\beta_j})$, then $s(\mathrm{A}_1, \mathrm{A}_2) = 0.5$.
5) If $\alpha_j = \overline{\beta_j}$, then $s(\mathrm{A}_1, \mathrm{A}_2) = 0$.

It can be proven as in Theorem 1.

Definition 11. Let $\mathrm{A}_1 = \{\alpha_1, \alpha_2, \dots, \alpha_n\}$ and $\mathrm{A}_2 = \{\beta_1, \beta_2, \dots, \beta_n\}$ INSs, then the weighted similarity measure between A_1, A_2 is defined as follows:

$$S_w(\mathrm{A}_1, \mathrm{A}_2) = \sum_{j=1}^{n} w_j \frac{D(\alpha_j, \overline{\beta_j})}{D(\alpha_j, \beta_j) + D(\alpha_j, \overline{\beta_j})} \qquad (6)$$

In here the weight w_j $\left(w_j \in [0,1], \sum_{j=1}^{n} w_j = 1\right)$ for each element α_j or β_j $(j = 1,2, \dots, n)$ satisfies properties (1-5).

If $w = (1/n, 1/n, \dots, 1/n)^T$, then Equation (6) reduces to Equation (5) as follows:

$$S_w(\mathrm{A}_1, \mathrm{A}_2) = \sum_{j=1}^{n} \frac{1}{n} \frac{D(\alpha_j, \overline{\beta_j})}{D(\alpha_j, \beta_j) + D(\alpha_j, \overline{\beta_j})}$$

$$= \frac{1}{n} \sum_{j=1}^{n} \frac{D(\alpha_j, \overline{\beta_j})}{D(\alpha_j, \beta_j) + D(\alpha_j, \overline{\beta_j})} = s(\mathrm{A}_1, \mathrm{A}_2)$$

A MCDM Method Based on Similarity Measure

Now, a method for MCDM problem will be presented by using the similarity measure developed between INSs.

Let $A = \{A_1, A_2, \dots, A_m\}$ be an alternatives set and $C = \{C_1, C_2, \dots, C_n\}$ be the criteria set. Assume that the weight of the criterion C_j $(j = 1,2, \dots, n)$, given by decision maker, is w_j, $w_j \in [0,1]$ and $\sum_{j=1}^{n} w_j = 1$. The characteristic of alternative A_i $(i = 1,2, \dots, m)$ is given by;

$$A_i = \left\{\langle x, \left[T_{A_i}^L(C_j), T_{A_i}^U(C_j)\right], \left[I_{A_i}^L(C_j), I_{A_i}^U(C_j)\right], \left[F_{A_i}^L(C_j), F_{A_i}^U(C_j)\right]\rangle : C_j \in C\right\}$$

where $0 \leq T_{A_i}^U(C_j) + I_{A_i}^U(C_j) + F_{A_i}^U(C_j) \leq 3, T_{A_i}^U(C_j) \geq 0, I_{A_i}^U(C_j) \geq 0, F_{A_i}^U(C_j) \geq 0$, $(i = 1,2, \dots, m), (j = 1,2, \dots, n)$. Here $\left[T_{A_i}^L(C_j), T_{A_i}^U(C_j)\right]$ indicates the degree that the alternative A_i satisfies the criterion C_j, $\left[T_{A_i}^L(C_j), T_{A_i}^U(C_j)\right]$ indicates the degree that the alternative A_i is indeterminacy on the criterion C_j, $\left[F_{A_i}^L(C_j), F_{A_i}^U(C_j)\right]$ indicates the degree that the alternative A_i does not satisfy the criterion C_j.

For the rest of the paper $v_{ij} = \left([a_{ij}, b_{ij}], [c_{ij}, d_{ij}], [e_{ij}, f_{ij}]\right)$ will be used instead of $T_{A_i}(C_j), I_{A_i}(C_j), F_{A_i}(C_j)$ and decision matrix which consist of v_{ij} interval neoutosophic numbers will be denoted $R = (v_{ij})_{m \times n}$.

We suggest the decision making procedure as follows:

Step1. Obtain the decision matrix

Suppose that the decision matrix is defined by

$$R = \begin{matrix} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{matrix} \begin{bmatrix} C_1 & C_2 & \cdots & C_n \\ ([a_{11},b_{11}],[c_{11},d_{11}],[e_{11},f_{11}]) & ([a_{12},b_{12}],[c_{12},d_{12}],[e_{12},f_{12}]) & \cdots & ([a_{1n},b_{1n}],[c_{1n},d_{1n}],[e_{1n},f_{1n}]) \\ ([a_{21},b_{21}],[c_{21},d_{21}],[e_{21},f_{21}]) & ([a_{21},b_{21}],[c_{21},d_{21}],[e_{21},f_{21}]) & \cdots & ([a_{2n},b_{2n}],[c_{2n},d_{2n}],[e_{2n},f_{2n}]) \\ \vdots & \vdots & \vdots & \vdots \\ ([a_{m1},b_{m1}],[c_{m1},d_{m1}],[e_{m1},f_{m1}]) & ([a_{m2},b_{m2}],[c_{m2},d_{m2}],[e_{m2},f_{m2}]) & \cdots & ([a_{mn},b_{mn}],[c_{mn},d_{mn}],[e_{mn},f_{mn}]) \end{bmatrix}$$

whose elements are INNs.

Step 2. Calculate the ideal alternative.

Assessment criteria are generally classified into two categories: benefit and cost criteria.

Ideal alternative is obtained as follow:

$$A^* = \upsilon_j = \left([a_j,b_j],[c_j,d_j],[e_j,f_j]\right) = \begin{cases} ([1,1],[0,0],[0,0]), & \text{for benefit criteria,} \\ ([0,0],[1,1],[1,1]), & \text{for cost criteria,} \end{cases}$$

$j = 1,2,\ldots,n.$

Step 3. Calculate the similarity between the ideal alternative and each alternative.

For this purpose it is obtained by;

$$S_w^t(A^*,\mathrm{A}_i) = \sum_{j=1}^{n} w_j \frac{D(\upsilon_j,\overline{\upsilon_{\iota j}})}{D(\upsilon_j,\upsilon_{ij})+D(\upsilon_j,\overline{\upsilon_{\iota j}})} \, . \, (t = 1,2) \tag{7}$$

Here $S_w^1(A^*,\mathrm{A}_i)$ and $S_w^2(A^*,\mathrm{A}_i)$ are obtained by using Hamming and Euclidean distances, respectively.

Step 4. Rank the alternatives.

For decision analysis, the optimal choice is made according to this obtained result.

Numerical Example

In this section, the MCDM problem given by Ye (2014a) will be examined to demonstrate the efficacy of the developed method.

Let us consider an investment company that wants to invents a sum of money in the best option from the alternatives (1) A_1 is a car company (2) A_2 is a food company (3) A_3 is a computer company (4) A_4 is an arm company, under three criteria (1) C_1 is the risk analysis (2) C_2 is the growth analysis (3) C_3 is the environmental impact analysis. In here C_1 and C_2 are benefit criteria; C_3 is cost criterion. The weight vector of the criteria is $w = (0.35,0.25,0.40)$.

Let us consider the following decision matrix R whose elements are given by INNs.

$$R = \begin{matrix} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{matrix} \begin{bmatrix} C_1 & C_2 & C_3 \\ ([0.4,0.5],[0.2,0.3],[0.3,0.4]) & ([0.4,0.6],[0.1,0.3],[0.2,0.4]) & ([0.7,0.9],[0.2,0.3],[0.4,0.5]) \\ ([0.6,0.7],[0.1,0.2],[0.2,0.3]) & ([0.6,0.7],[0.1,0.2],[0.2,0.3]) & ([0.3,0.6],[0.3,0.5],[0.8,0.9]) \\ ([0.3,0.6],[0.2,0.3],[0.3,0.4]) & ([0.5,0.6],[0.2,0.3],[0.3,0.4]) & ([0.4,0.5],[0.2,0.4],[0.7,0.9]) \\ ([0.7,0.8],[0.0,0.1],[0.1,0.2]) & ([0.6,0.7],[0.1,0.2],[0.1,0.3]) & ([0.6,0.7],[0.3,0.4],[0.8,0.9]) \end{bmatrix}$$

By using Equation (2) and Equation (7), $S_w^1(A^*,A_i)$ $(i = 1,2,3,4)$ can be obtained as follows:

$$S_w^1(A^*,A_1) = 0.5025$$
$$S_w^1(A^*,A_2) = 0.6900$$
$$S_w^1(A^*,A_3) = 0.5983$$
$$S_w^1(A^*,A_4) = 0.6958$$

so the ranking order of alternatives is

$$A_4 \succ A_2 \succ A_3 \succ A_1.$$

Obviously A_4 is the best one.

By using Equation (3) and Equation (7), $S_w(A^*, A_i)$ $(i = 1,2,3,4)$ evaluated as:

$$S_w^2(A^*, A_1) = 0.5012$$
$$S_w^2(A^*, A_2) = 0.6766$$
$$S_w^2(A^*, A_3) = 0.5897$$
$$S_w^2(A^*, A_4) = 0.7111$$

therefore the ranking order of alternatives is

$$A_4 \succ A_2 \succ A_3 \succ A_1.$$

A_4 is also the best one.

With regard tothe method in (Şahin,2015), the same final ranking result is obtained. But the easy applicability of this method makes it more advantageous than the other. Moreover, the result is same as (Ye, 2014a) according to Hamming distance measure. This demonstrates the effectiveness of the proposed method.

CONCLUSION

In this article, the Hamming and Euclidean distances-based similarity measure is extended to interval neotrosophic set. Then, by using this similarity measure, the best alternative is identified. To demonstrate the applicability and effectiveness of the proposed method, we compare the ranking results with others.

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