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NEUTROSOPHIC FUZZY MAGDM USING ENTROPY GUIDED METHOD

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ABSTRACT

The MAGDM problems have investigated under neutrosophic fuzzy environment, and proposed an approach to handling the situations where the attribute values were characterized by fuzzy sets, intuitionistic fuzzy sets, vague sets, and soft sets in which the information about attribute weights were completely unknown. In this directions, each object of fuzzy set (FS) theory is assigned a single real value, called the grade of membership, between zero and one [Zadeh, 1965, 1978, 1983]; Kaufmann & Gupta, 1985]; [Kwang - Lee, 2005]; and [Zimmermann, 1991]. Atanassov [1986, 1989, 1999] introduced the concept of intuitionistic fuzzy set (IFS) characterized by a membership function and a non-membership function, which is a generalization of the concept of fuzzy set whose basic component is only a membership function. The intuitionistic fuzzy set has received much attention since its appearance. Gau & Buehrer [1994] introduced the concept of the vague set. But Bustince & Burillo [1996] showed that vague sets are intuitionistic fuzzy sets. The proposed approach first fuses all individual neutrosophic fuzzy decision matrices into the collective neutrosophic fuzzy decision matrix by using the NFOWA operator. Then the obtained attribute weights and the NFHA operator have used to get the overall neutrosophic fuzzy values of alternatives The ordered weighted averaging (OWA) operator has attracted much interest among researches. It provides a general class of parameterized aggregation operators that include the min, max and the average. Many applications in different areas such as decision making, expert systems, data mining, approximate reasoning fuzzy system and control utilize the OWA aggregation. One of the appealing points in OWA operators is the concept of orness. The orness measure reflects the and-like or or-like aggregation characteristic of an OWA operator, which is very important both in theory and applications. The orness of OWA operator is also called "attitudinal character" to represent the aggregation performance information. It is clear that the actual type of aggregation performed by an OWA operator depends upon the form of the weighting vector.

SECTION-1: PREVIOUS LITERATURES

Gau & Buehrer [1994] pointed out that the drawback of using the single membership value in fuzzy set theory is that the evidence for $u \in U$ and the evidence against $u \in U$ are in fact mixed together (U is the universe of discourse and u is an element of U). To tackle this problem Gau & Buehrer [1994] proposed the notion of Vague Sets (VSs), which allow using interval-based membership instead of using point-based membership as in FSs.

The interval-based membership generalization in VSs is more expressive in capturing data vagueness. However, VSs are shown to be equivalent to that of intuitionistic fuzzy sets (IFSs) [Bustince & Burillo, 1996]. For this reason, interesting features for handling vague data that are unique to VSs are largely ignored. Lu & Ng [2004, 2005, 2009] pointed out the major differences between IFSs and VSs by the way their interval memberships are defined.

Vagueness and uncertainty are the two important aspects of imprecision. IFS is an intuitively straight forward extension of Zadeh's [1965] fuzzy sets. IFS theory basically defies the claim that from the fact that an element x "belongs" to a given degree (say μ) to a fuzzy set A, it naturally follows that x should "not belong" to A to the extent $1-\mu$, an assertion implicit in the concept of a fuzzy set. On the contrary, IFSs assigns to each element of the universe both a degree of membership μ and one of non-membership γ such that $\mu + \gamma \leq 1$, thereby relaxing enforced duality $\gamma = 1 - \mu$ from fuzzy set theory.

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Obviously, when $\mu + \gamma = 1$ for all elements of the universe, the traditional fuzzy set concept is recovered. In IFS this identity is weakened into an inequality, or in other words: a denial of the law of the excluded middle occurs, one of the main ideas of intuitionism. Let *X* be the universe of discourse defined by $X = \{x_1, x_2, \ldots, x_n\}$ The grade of membership of an element $x_i \in X$ in a fuzzy set is represented by real values between 0 and 1. It indicates the evidence for $x_i \in X$, but not the evidence against $x_i \in X$.

Atanassov [1986, 1989] pointed out that this single value combines the evidence for $x_i \in X$ and the evidence against $x_i \in X$. An IFS "*A*" in *X* is characterised by a membership function $\mu_A(x_i)$ and a non-membership function $\gamma_A(x_i)$. Here, $\mu_A(x_i)$ and $\gamma_A(x_i)$ are associated with each point in *X*, a real number in [0,1] with the values of $\mu_A(x_i)$ and $\gamma_A(x_i)$ at *X* representing the grade of membership and non-membership of x_i in *A*. Thus closeness of the value of $\mu_A(x_i)$ to unity and the value of $\gamma_A(x_i)$ to zero, raise high the grade of membership and lower the grade of non-membership of x_i. An IFS becomes a fuzzy set when $\gamma_A(x_i) = 0$

The OWA Operator 1.1: An OWA operator of dimension n ($n \geq 2$) is a map $F_W: R^n \to R$ that has an associated weighting vector $W = (w_1 + w_2 + \ldots + w_n)$ having $(w_1 + w_2 + \ldots + w_n) = 1$ where $0 \leq w_i \leq 1$ (i varies 1 to n). In addition, $FW(X) = F_W(x_1, x_2, \ldots, x_n) = \sum_{j=1}^{n} w_i y_i$ with y_i being ith largest of x_i's.

Definition 1.2: The degree of "orness" associated with this operator is defined as Orness (*W*) = $\sum_{i=1}^{n} \frac{(n-i)}{(n-1)} w_i$.

Definition 1.3: The max, min and average correspond to W^*, W_*, W_A, respectively, where $W^* = (1, 0, 0\ldots,0)$,
$W_* = (1,0,0\ldots,0)$, $WA = (1/n,/1/n, \ldots, 1/n)$, and $F_{W^*}(X) = \min_{0 \leq i \leq 1} \{xi\}$; $F_{W^*}(X) = \min 0 \leq i \leq 1 \{xi\}$; $F_{W_A} = (1/n) \sum_{i=1}^{n} x_i$. Obviously, orness ($W^*$) = 1; orness ($W_*$) = 0; orness ($W_A$) = ½.

SECTION-2: QUANTIFIER GUIDED AGGREGATIONS WITH OWA OPERATORS

Consensus processes imply that experts achieve an agreement about a problem before taking a decision, thus yielding a solution accepted by the organization, society or themselves. Various consensus approaches were proposed ranging from rigid methods to flexible approaches [Kacprzyk, 1986, 1987]. In these approaches, it is crucial to establish a consensus measure to calculate the level of agreement. Consensus measures are indicators to evaluate how far a group of experts' opinions is from unanimity.

Mohanty & Bhasker [2005] have applied the concepts of Linguistic Quantifiers in the product classifications based on customer preference in Internet-Business. In this work, The Linguistic Quantifiers guided aggregation based on the Ordered Weighted Averaging (*OWA*) operators are used to derive the weights of the experts.

The problem of determining weights for an *OWA* operator can be addressed in different ways, for example with the use of the so-called 'Linguistic Quantifiers' introduced by Zadeh [1983]. A relative linguistic quantifier *Q*, such as 'most', 'few', 'many', and 'all', can be represented as a fuzzy subset of the unit interval, where for a given proportion $r \in [0,1]$ of the total of the values to aggregate, *Q*(*r*) indicates the extent to which this proportion satisfies the semantics defined in *Q*. For example, given *Q* = 'most', if *Q*(0.7) = 1 then it would mean that a proportion of 70% totally satisfies the idea conveyed by the quantifier 'most', whereas *Q*(0.55) = 0.25 indicates that the proportion 55% is barely compatible with this concept (only 25%).

Regular Increasing Monotone (RIM) quantifiers [Liu, 2008; Liu & Han, 2008] are especially interesting for their use in *OWA* operators. These quantifiers present the following properties: (a). *Q*(0) = 0; (b). *Q*(1) = 1; (c). If $r_1 < r_2$ then $Q(r_1) \geq Q(r_2)$.

Definition 2.1: Yager [1988] suggested the following method to compute weights w_i, with the use of a RIM quantifier *Q*: $w_i = Q(1/n) - Q((i-1)/n)$, i varies from 1 to n.

where the membership function of a linear RIM quantifier *Q*(*r*) is defined by two parameters $a, b \in [0,1]$ as:

Q(r) = 0, r < a; (r-a)/(b-a), a ≤ r ≤ b; 1, r > b.

Example 2.2: RIM quantifier *Q* = 'most', with *a* = 0.5 and *b* = 0.7 is given as: Q(r) = 0, r < 0.5; 5r – 2.5, 0.5 ≤ r ≤ 0.7; r > 0.7.

Since the use of *OWA* with RIM quantifiers captures the notion of the soft consensus correctly, they can be adopted for the purpose of studying the effect of different aggregation operators on the resolution of a consensus problem with many experts, and expressing a desired group's attitude.

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Yager [1988] proposed a method for obtaining the OWA weighting vectors via fuzzy linguistic quantifiers; in particular the Regular Increasing Monotone (RIM) quantifiers, which can provide information aggregation procedures guided by linguistically expressed concepts and a dimension- independent description of the desired aggregation.

Definition 2.4: A fuzzy subset Q of the real line is called a RIM quantifier if the membership function $Q(x)$ obeys $Q(0) = 0$, $Q(1) = 1$ and $Q(x) \geq Q(y)$ for $x > y$.

Example 2.5: RIM quantifier are "all", "most", "many", "at least". The quantifier "all" is represented by the fuzzy subset $Q^*(x) = 1, x=1; 0, x \neq 1$. The quantifier "there exists, not none", is defined as $Q^*(x) = 0, x = 0; 1, x \neq 0$.

With a RIM quantifier Q, Yager (1988) proposed the OWA weighting vector generating rule:
$w_i = Q(1/n) - Q((i-1)/n)$, (2)

Definition 2.6: Therefore, the quantifier guided aggregation with OWA operator is
$F_Q(X) = F_W(X) = \sum_{j=1}^{n} Q\left(\frac{i}{n}\right) - Q(\frac{i-1}{n}) y_i$ (3)

Definition (orness) 2.7: Yager [1988] also extended the orness measure of OWA operator, and defined the orness of a RIM quantifier: Orness (Q) = $\sum_{i=1}^{n} \frac{(n-i)}{(n-1)} \left(Q\left(\frac{i}{n}\right) - Q(\frac{i-1}{n})\right)$ as n tends to ∞ = $1/(n-1)\sum_{i=1}^{n-1} Q(\frac{i}{n})$ as n tends to ∞ = $\int_0^1 Q(x)dx$ (4)

SECTION 3: THE FUZZY LINGUISTIC QUANTIFIER FOR MAGDM

The aggregation weighted vector W is a mapping to membership function $Q(r)$ guided by a monotonically non-decreasing fuzzy linguistic quantifier, Q represented as equation (5) and (6). The membership function $Q(r)$ represents the membership grade on r that belongs to Q.

Definition 3.1: The membership function also differs from Q (Herrera et al., 2000).
$w_k = Q(k/n) - Q((k-1) / n) (1/2)$ (5)
$Q(r) = 0, r < a$; $(r-a) / (b-a), a \leq r \leq b$ where a, b, r are in [0, 1]; 1, $r > b$. (6)

To enable the use of different fuzzy linguistic quantifiers to aggregate behaviour among attributes to produce the fuzzy majority rule the following perspectives are considered. "Critical" factor is used for fuzzy linguistic quantifier "At least half" to emphasize the strong influence of aggregating on results. "Major" factor is used for fuzzy linguistic quantifier "Most" to emphasize the medium influence of aggregation on the results. Finally, "Fundamental" factor is used for fuzzy linguistic quantifier "As many as possible" to represent the degree to which essential requests are satisfied.

Optimizing the aggregation weighting vector 3.2:

Optimizing the aggregation weighted vector requires calculating the degree of "Orness" and "Entropy" (Dispersion). The calculation is based on the aggregation weighted vector W, displayed in equations (7) and (8). Orness, which lies in the unit interval, is a good measurement for characterizing the degree to which the aggregation is an Or-like (Max-like) or And-like (Min-like) operation. When Orness equals 1, the aggregation equals the maximum operation; when equals 0, the aggregation equals the minimum operation; and when Orness equals 0.5, the aggregation equals the arithmetic mean operation.

Simultaneously, Entropy represents the measurement for characterizing the degree to which information on the individual behaviours in the aggregation process is used (Yager, 1988).

Orness (W) = (1 / (n-1) $\sum_{i=1}^{n} (n-k) w_k$ (7)

Entropy (W) = (-) $\sum_{i=1}^{n} w_k \ In\ w_k$ (8)

Optimization Problem 3.3:

Maximize (-) $\sum_{i=1}^{n} w_k \ In\ w_k$ (9)

subject to:

Orness (W) = (1 / (n-1) $\sum_{i=1}^{n} (n-k) w_k$ (9a)

$\sum_{k=1}^{n} w_k = 1$; w_k is in [0, 1] for all k varying from 1 to n. (9b)

Furthermore, the Langrange multiplier method can be used to obtain the maximal Entropy aggregation weighted vector W^*, which can aggregate the maximum information from behaviours. Filev & Yager, (1998) presented a detailed information in this regard. Equation (9) can be further simplified as equations (10) and (11). Moreover, the numerical analysis approach can be used to obtain b from equation (10), and can be substituted into equation (11) to obtain W^*. The initial vector of W thus is replaced by the new W^*, thus optimizing the aggregation weighted vector.

$\sum_{k=1}^{n} \frac{n-k}{n-1}$ – Orness (W)) $b^{(n-k)} = 0$ (10)

$$W_k^* = \frac{b^{n-k}}{\sum_{k=1}^{n} b^{n-k}} \quad (11)$$

Step-2: Derive the weights by Quantifier (RIM) guided entropy method with Orness – for weights by using

w_k = Q(k/n) – Q((k-1) / n) (1/2) k varies from 1 to n (5)

Q(r) = 0, r < a;

= (r-a) / (b-a), a ≤ r ≤ b where a, b, r are in [0, 1];

= 1, r > b. (6)

Orness (W) = (1 / (n-1) $\sum_{i=1}^{n}(n-k)w_k$ (9a)

$\sum_{k=1}^{n} w_k$ = 1; w_k is in [0, 1] for all k varying from 1 to n. (9b)

Hence Maximize (-) $\sum_{i=1}^{n} w_k \ \ In\, w_k$ (9)

subject to the constraints

Orness (W) = (1 / (n-1) $\sum_{i=1}^{n}(n-k)w_k$. (9a)

$\sum_{k=1}^{n} \frac{n-k}{n-1}$ – Orness (W)) $b^{(n-k)}$ = 0 (10)

$$W_k^* = \frac{b^{n-k}}{\sum_{k=1}^{n} b^{n-k}} \quad (11)$$

SECTION-4: THE ALGORITHM FOR GETTING WEIGHTS BY QUANTIFIER (RIM) GUIDED ENTROPY METHOD

Definition 4.1: A neutrosophic fuzzy set A on the universe of discourse X characterized by a truth membership function $T_A(x)$, an indeterminacy function $I_A(x)$ and a falsity membership function $F_A(x)$ is defined as A = { < x, $T_A(x)$, $I_A(x)$, $F_A(x)$ > : x ∈ X }, where T_A, I_A ,F_A : X → [0. 1] and $0 \le T_A(x) \le 1$; $0 \le I_A(x) \le 1$; $0 \le F_A(x) \le 1$, for all x ∈ X.

Steps for an algorithm 4.2:

Step-1: Calculate the weight information using the Quantifier guided aggregations..

To derive a weight vector w by using Quantifier (RIM) guided entropy method with orness for weight.

Most Quantifier: Q(r) = 0, r < 03;

= (r – 0.3) / (0.8 – 0.3), 0.3 ≤ r ≤ 0.8 where a, b, r are in [0, 1];

= 1, r > 0.8. (6)

Further it follows that Maximize (-) $\sum_{i=1}^{n} w_k \ \ In\, w_k$

subject to the constraints

Orness (W) = (1 / (n-1) $\sum_{i=1}^{n}(n-k)w_k$

$\sum_{k=1}^{n} w_k$ = 1; w_k is in [0, 1] for all k varying from 1 to n

$\sum_{k=1}^{n} \frac{n-k}{n-1}$ – Orness (W)) $b^{(n-k)}$ = 0

$$W_k^* = \frac{b^{n-k}}{\sum_{k=1}^{n} b^{n-k}}$$

Now the following calculations are derived when n = 5.

$$w_1^* = \frac{b^4}{\sum_{j=1}^{5} 5-j} = \frac{b^4}{b^4+b^3+b^2+b+1}$$

$$w_2^* = \frac{b^3}{\sum_{j=1}^{5} 5-j} = \frac{b^3}{b^4+b^3+b^2+b+1}$$

$$w_3^* = \frac{b^2}{\sum_{j=1}^{5} 5-j} = \frac{b^2}{b^4+b^3+b^2+b+1}$$

$$w_4^* = \frac{b}{\sum_{j=1}^{5} 5-j} = \frac{b}{b^4+b^3+b^2+b+1}$$

$$w_5^* = \frac{1}{\sum_{j=1}^{5} 5-j} = \frac{1}{b^4+b^3+b^2+b+1}$$

Now other deviations are given below:

W_1 = Q(1/5)- Q(0/5) = Q(0.2) – Q(0) = 0 - 0 = 0.

W_2 = Q(2/5)- Q(1/5) = Q(0.4) – Q(0.2) = 0.2 - 0 = 0.2 .

W_3 = Q(3/5)- Q(2/5) = Q(0.6) – Q(0.4) = 0.6 – 0.2 = 0.4 .

W_4 = Q(4/5)- Q(3/5) = Q(0.8) – Q(0.6) = 1 – 0.6 = 0.4 .

W_5 = Q(5/5)- Q(4/5) = Q(1) – Q(0.8) = 1 – 1 = 0 .

Thus Orness (W) = (1 / (5-1) $\sum_{j=1}^{n}(5-j)w_j$

= (1/4) ($4w_1 + 3w_2 + 2w_3 + w_4$)

= (1/4) (4(0) + 3(0.2) + 2(0.4) + (0.4)) = 0.45.

Also $\sum_{j=1}^{5} \frac{5-j}{5-1} - 0.45) b^{(5-j)} = 0$

Then $(\frac{5-1}{5-1} - 0.45)b^4 + (\frac{5-2}{5-1} - 0.45)b^3 + (\frac{5-3}{5-1} - 0.45)b^2 + (\frac{5-4}{5-1} - 0.45)b + (\frac{5-5}{5-1} - 0.45) = 0.$

Implies that $(\frac{4}{4} - 0.45)b^4 + (\frac{3}{4} - 0.45)b^3 + (\frac{2}{4} - 0.45)b^2 + (\frac{1}{4} - 0.45)b + (\frac{0}{4} - 0.45) = 0.$

Implies that $0.55\, b^4 + 0.3\, b^3 + 0.05\, b^2 - 0.2\, b - 0.45 = 0.$

From the formulae, $w_1^* = \frac{b^4}{\sum_{j=1}^{5} 5-j} = \frac{b^4}{b^4+b^3+b^2+b+1}$

$$w_2^* = \frac{b^3}{\sum_{j=1}^{5} 5-j} = \frac{b^3}{b^4+b^3+b^2+b+1}$$

$$w_3^* = \frac{b^2}{\sum_{j=1}^{5} 5-j} = \frac{b^2}{b^4+b^3+b^2+b+1}$$

$$w_4^* = \frac{b}{\sum_{j=1}^{5} 5-j} = \frac{b}{b^4+b^3+b^2+b+1}$$

$$w_5^* = \frac{1}{\sum_{j=1}^{5} 5-j} = \frac{1}{b^4+b^3+b^2+b+1}$$

Hence it finds that $w_1^* = 0.1619$; $w_2^* = 0.1791$; $w_3^* = 0.1979$; $w_4^* = 0.2189$; $w_1^* = .2421$.

Step-2: Utilize the NFOWA operator to aggregate all individual neutrosophic fuzzy decision matrices $R^{(k)} = < (T_{ij}(k), I_{ij}(k), F_{ij}(k) > = (r_{ij}^{(k)})$ (k varies from 1, 2,3, and 4) into a collective neutrosophic fuzzy decision matrix $R = (r_{ij})_{m \times n}$.

Step-3: Use the NFHA operator to get the overall values r_j of the alternatives O_j (j = 1, 2,…,n) using the weights 0.2717, 0.2254, 0.2608, 0.2421 by funding from Poisson distribution through a method of fitness.

Step-4: Using r* = (1,0,0) = (T_A*, I_A*, F_A*), find $d(r^*, r_j) = \sqrt{\left(T_A{}^* - T_{j_A}\right)^2 + \left(I_A{}^* - I_{j_A}\right)^2 + \left(F_A{}^* - F_{j_A}\right)^2}$ to calculate the distances between informational neutrosophic values $r_j = (T_{j_A}, I_{j_A}, F_{j_A})$ (j = 1, 2 ,..., n).

Step-5: Rank the alternatives based on distances.

Step-6: Select the best alternative.

Section 5 - Numerical Illustration:

Step-1: Assume that the information in decision making are in neutrosophic fuzzy matrices as follows:

$$R^1 = \begin{bmatrix} <0.25,0.54,0.8> & <0.3,0.4,0.9> & <0.7,0.35,0.5> & <0.9,0.2,0.8> \\ <0.6,0.5,0.5> & <0.6,0.2,0.3> & <0.2,0.4,0.9> & <0.6,0.23,0.7> \\ <0.3,0.45,0.9> & <0.7,0.1,0.4> & <0.6,0.5,0.5> & <0.4,0.2,0.9> \\ <0.45,0.38,0.27> & <0.37,0.68,0.16> & <0.6,0.25,0.3> & <0.1,0.4,0.8> \end{bmatrix}$$

$$R^2 = \begin{bmatrix} <0.1,0.3,0.7> & <0.6,0.6,0.5> & <0.4,0.2,0.1> & <0.3,0.7,0.6> \\ <0.3,0.55,0.37> & <0.75,0.42,0.1> & <0.32,0.67,0.56> & <0.35,0.56,0.72> \\ <0.5,0.4,0.32> & <0.65,0.25,0.32> & <0.6,0.3,0.1> & <0.75,0.25,0.55> \\ <0.27,0.9,0.81> & <0.31,0.4,0.6> & <0.75,0.65,0.55> & <0.3,0.7,0.9> \end{bmatrix}$$

$$R^3 = \begin{bmatrix} <0.32,0.47,0.6> & <0.9,0.1,0.3> & <0.6,0.4,0.5> & <0.3,0.5,0.7> \\ <0.12,0.32,0.52> & <0.17,0.81,0.9> & <0.5,0.3,0.1> & <0.45,0.65,0.27> \\ <0.50,0.6,0.23> & <0.56,0.52,0.23> & <0.3,0.6,0.1> & <0.57,0.52,0.55> \\ <0.54,0.83,0.72> & <0.73,0.86,0.61> & <0.5,0.52,0.4> & <0.6,0.4,0.2> \end{bmatrix}$$

$$R^4 = \begin{bmatrix} <0.7,0.3,0.1> & <0.5,0.4,0.4> & <0.2,0.1,0.6> & <0.7,0.9,0.6> \\ <0.3,0.56,0.73> & <0.57,0.24,0.1> & <0.23,0.76,0.65> & <0.53,0.65,0.27> \\ <0.32,0.32,0.6> & <0.56,0.52,0.32> & <0.1,0.3,0.9> & <0.57,0.52,0.55> \\ <0.72,0.5,0.18> & <0.13,0.6,0.4> & <0.55,0.56,0.78> & <0.7,0.1,0.6> \end{bmatrix}$$

$$R^5 = \begin{bmatrix} <0.52,0.45,0.1> & <0.57,0.37,0.1> & <0.76,0.65,0.23> & <0.57,0.52,0.55> \\ <0.3,0.6,0.7> & <0.7,0.4,0.1> & <0.3,0.7,0.6> & <0.5,0.4,0.6> \\ <0.2,0.3,0.2> & <0.6,0.2,0.5> & <0.1,0.6,0.65> & <0.3,0.9,0.7> \\ <0.27,0.5,0.81> & <0.75,0.25,0.32> & <0.32,0.67,0.56> & <0.35,0.56,0.72> \end{bmatrix}$$

Step-3: Utilize the NFOWA operator to aggregate all individual neutrosophic fuzzy decision matrices $R^{(k)} = \langle T_{ij}(k), I_{ij}(k), F_{ij}(k) \rangle = (r_{ij}^{(k)})$ (k varies from 1, 2,3, and 4) into a collective neutrosophic fuzzy decision matrix $R = (r_{ij})_{m \times n}$ using weight vector W = {0.1619,0.1791,0.1979,0.2189,0.2421}.

R=

$$\begin{bmatrix} <0.4418,0.5838,0.4935> & <0.6443,0.6118,0.4941> & <0.5778,0.6138,0.5750> & <0.6229,0.3427,3475> \\ <0.3310,0.4804,0.3991> & <0.5974,0.4626,0.5594> & <0.3202,0.3845,0.3707> & <0.4919,0.4720,0.4602> \\ <0.3672,0.5825,0.4732> & <0.6121,0.6514,0.6339> & <0.3506,0.5182,0.4024> & <0.5366,0.3863,0.3197> \\ <0.4841,0.3134,0.3514> & <0.5354,0.3924,0.5577> & <0.4841,0.4369,0.4351> & <0.4675,0.5372,0.2934> \end{bmatrix}$$

Step-4: **U**sing the weights w = {0.2717, 0.2608, 0.2254, 0.2421} obtained from Poisson distribution. New reduced row matrix R is [(0.4106, 0.4943, 0.5646), (0.6009, 0.4526, 0.4362), (0.4664, 0.4978, 0.5436), (0.5374, 0.5644, 0.6443)].

Step-5: $d = \sqrt{\frac{1}{2}[\sum[(1-T)^2 + (0-I)^2 + (0-F)^2]]}$.

$d(r, r_1) = 0.6758 = A_1$; $d(r, r_2) = 0.5264 = A_2$; $d(r, r_3) = 0.6434 = A_3$; $d(r, r_4) = 0.6882 = A_4$

Step-6: $A_4 > A_1 > A_3 > A_2$.

Step-7: A_4 is best alternative.

CONCLUSIONS

The proposed approach in this work not only can comfort the influence of unjust arguments on the decision results, but also avoid losing or distorting the original decision information in the process of aggregation. Thus, the proposed approach provides us an effective and practical way to deal with multi-person multi-attribute decision making problems, where the attribute values are characterized by NFSs and the information about attribute weights is partially known. The suitable alternative is selected through the algorithm from the given neutrosophic information in which the unknown weights are derived based upon normal distribution.

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