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Research paper

Analysis of Faculty Teaching using Multi-criteria Decision Making Approach

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Abstract

In order to maintain a good standardof any college, the institution should follow paper based approach or web-based approach to gather student feedback on faculty teaching to maintain the qualities of the faculty. Students have very much concerned about their teachers who have played a vital role in their life in both outside or inside of the institutions which helps them to justify a teacher and it comes in form of their feedback. In this paper, we introduce a ranking method of the given feedback's factors of teacher's performances with the help of multi-criteria decision making approach using neutrosophic logic. We use the score and accuracy functions and the hybrid score-accuracy functions of single valued neutrosophic numbers (SVNNs) and ranking method for SVNNs.

Keywords*: Feedback system; hybrid score accuracy function; single valued neutrosophic number; neutrosophic set*

1. Introduction

On the basis of fuzzy set[8], the concept of intuitionistic fuzzy set (IFS) introduced by Attanasov[5] by connecting a membership function$T_B(y)$, non-membership function $F_B(y)$ in intuitionistic fuzzy sets, and they satisfy the conditions $T_B(x), F_B(x) \in [0,1]$ and $0 \leq T_B(x) + F_B(y) \leq 1$. Further, interval-valued intuitionistic fuzzy set (IVIFS) proposed by Atanassov and Gargov [6], by extending the membership values to interval numbers. However, IFSs, and IVIFSs cannot describe and deal with the indeterminate and inconsistent information that exists in real world. Later Smarandache [2] proposed the new concept of a neutrosophic set which is generalization of different type of FSs and IFSs for handling uncertain, imprecise, incomplete, and inconsistent information. Single valued neutrosophic set (SVNs) and an interval neutrosophic set (INS), which are the subclasses of a neutrosophic set. Later Ye [3,4] defined the similarity measures between interval neutrosophic sets (INSs)and finding the similarity measures between each alternative and ranking those alternative to find out the best one. The process of multi-criteria decision making (MCDM), the criterion values of any situations take the form of single valued neutrosophic sets (SVNSs) or intervalneutrosophic sets (INSs).Liang and Wang [11] studied fuzzy multi-criteria decision making (MCDM) algorithm for personnel selection. Karsak [1] presented fuzzy MCDM approach based on ideal and anti-ideal solutions for the selection of the most suitable candidate. Dursun and Karsak [10] discussed fuzzy MCDM approach by using TOPSIS . Ehrgott and Gandibleux [9] presented a comprehensive survey of the state of the art in MCDM.

In recent years feedback system is very essential for many institutes. This system can help us to improve the teacher's performance skill, techniques, teaching style and many more. Feedback system contains various factor like "Timeliness", "Communication skill", "Control of the class" etc.In this paper, we have used a multicriteria group decision making approach for the feedback system and use unknown weights based on score and accuracy functions, hybrid score accuracy functions under neutrosophicenvironement. The paper is organized in five sections. Section two represent the basic definition of neutrosophic set. Section three describes multi-criteria group decision making. Section four gives the mathematical approaches of hybrid-score accuracy functions on our discussed problem. Finally, section five draws conclusions based on our study.

2. Preliminaries

The concept of a neutrosophic set introduced by Smarandache [4] which generalizes the form of fuzzy set, IFS, and IVIFS etc.

2.1. Neutrosophic Set

Let M be a space of points (objects), with a generic element in M denoted by m. A neutrosophic set S in M is characterized by a truth-membership function $T_S(m)$, an indeterminacy-membership function $I_S(m)$, and a falsity-membership function $F_S(m)$. The functions$T_S(m)$, $I_S(m)$ and $F_S(m)$ are real standard or nonstandard subsets of $]0,1[$, i.e. $T_S(m): X \to]0^-, 1^+[$, $I_S(m): M \to]0^-, 1^+[$, $F_S(m): M \to]0^-, 1^+[$. Hence, there is no restriction on the sum of $T_S(m,), I_S(m), F_S(m)$ and $0^{-1} \leq supT_S(m) + supI_S(m) + supF_S(m) \leq 3^+$.

2.2. Single valued neutrosophic sets

If $T_S(m)$, $I_S(m)$ and $F_S(m)$ are singleton subintervals/subsets in the real standard $[0,1]$, that is $T_S(m): M \to [0,1]$, $I_S(m): M \to [0,1]$ and $F_S(m): M \to [0,1]$. Then, a simplification of the neutrosophic set M is denoted by $M = \{\langle m, T_S(m), I_S(m), F_S(m)\rangle / m \in M\}$ which is called a SNS. It is a subclass of a neutrosophic set and includes SVNS and INS.

2.3. Single valued neutrosophic number (SNN)

For a SVNS S in M, the triple $\langle T_S(m), I_S(m), F_S(m)\rangle$ is called single valued neutrosophic number (SVNN), which is the fundamental element of a SVNS.

2.4. Complement of SVSNS

The complement of a SVNS S is denoted by S^C and defined as $T_S^c(m) = F_A(m), I_S^c(m) = 1 - I_S(m)$, $F_S^c(m) = T_S(m)$ for any s in M. Then, it can be denoted by the following form: $S^c = \{\langle m, T_S(m), 1 - I_A(x), F_A(x)\rangle / x \in X\}$. For two SVNSs S and U in M, two of their relations are defined as follows: A SVNS S is contained in the other SVNS U, $S \subseteq U$, if and only if $T_S(m) \le T_U(m), I_S(m) \ge I_U(m), F_S(m) \ge F_U(m)$ for any m in S.

2.5. Ranking methods for SVNNs valued neutrosophic number (SNN)

In this subsection, we define score function, accuracy function, and hybrid score-accuracy function of a SVNN, and the ranking method for SVNNs.

Let $S = \langle T(s), I(s), F(s)\rangle$ be a SVNN. Then, the score function and accuracy function of the SVNN can be presented, respectively, as follows:

$$s(m) = \big(1 + T(m) - F(m)\big)/2 \text{for} s(m) \in [0,1] \quad (1)$$

$$h(m) = \big(2 + T(m) - F(m) - I(m)\big)/3 \quad (2)$$

for h$(m) \in [0,1]$

For the score function of a SVNN a, if the truth-membership $T(m)$ is bigger and the falsity-membership $F(m)$ are smaller, then the score value of SVNN is greater. For the accuracy function of a SVNN, if the sum of $T(m)$, $1 - I(m)$and $1 - F(m)$ is bigger, then the statement is more affirmative, i.e. the accuracy function for SVNNs, two theorems are stated below.

Theorem 1.

For any two SVNNs m_1 and m_2 if $m_1 > m_2$ then $S(m_1) > S(m_2)$.

Theorem 2.

For any two SVNNs m_1 and m_2 if $S(m_1) = S(m_2)$ and $m_1 \ge m_2$then $h(m_1) \ge h(m_2)$. Based on theorem 1 and 2, a ranking method between SVNNs can be given by the following definition.

Let a_1 and a_2 be two SVNNs. Then the ranking method can be defined as follows.

(1) if$S(m_1) > S(m_2)$ then $m_1 > m_2$

(2) if$S(m_1) = S(m_2)$ and $h(m_1) \ge h(m_2)$ then $m_1 \ge m_2$ SVNS S in M, the triple $\langle T_S(m), I_S(m), F_S(m)\rangle$ is called single valued neutrosophic number (SVNN), which is the fundamental element of a SVNS.

3. Multi-criteria group decision-making methods

In a multi-criteria group decision-making problem, let $A = \{A_1, A_2, \dots, A_m\}$ be a set of alternatives and let $C = \{C_1, C_2, \dots, C_n\}$ be a set of attributes. The information about the weights of the decision makers is completely unknown and the information about the weights of the attributes is imprecisely in the group decision-making problem. Two methods developed based on the hybrid score-accuracy functions for multiple attribute group decision-making problems with unknown weights under single valued neutrosophic and interval neutrosophic environments

3.1. Multi-criteria group decision-making method in single valued neutrosophic setting

In the group decision process under single valued neutrosophic environment, if a group of t decision makers or experts is required in the evaluation process, then the kth decision maker can provide the evaluation information of the alternative $A_i (i = 1,2,\dots,m)$ on the attribute $C_j (j = 1,2,\dots,n)$, which is represented by the form of a SVNS: $A_i^k = \{\langle C_j, T_{A_i}^k(C_j), I_{A_i}^k(C_j), F_{A_i}^k(C_j)\rangle / C_j \in C\}$

Here $0 \le T_{A_i}^k(C_j) + I_{A_i}^k(C_j) + F_{A_i}^k(C_j) \le 3$, $T_{A_i}^k(C_j) \in [0,1], I_{A_i}^k(C_j) \in [0,1]$, $F_{A_i}^k(C_j) \in [0,1]$, for $k = 1,2,\dots,t, j = 1,2,\dots,n, i = 1,2,\dots,m$. For convenience, $a_{ij}^k = \langle T_{ij}^k, I_{ij}^k, F_{ij}^k\rangle$ is denoted as a SVNN in the SVNS. $A_i^k (k = 1,2,\dots,t; i = 1,2,\dots,m; j = 1,2,\dots,n)$. Therefore, we can get the k-th single valued neutrosophic decision matrix $D^k = \big(A_{ij}^k\big)_{m\times n} (k = 1,2,\dots,t)$. Then, the group decision-making method is described as follows.

Step 1: Calculate hybrid score-accuracy matrix

The hybrid score-accuracy matrix $H^k = \big(H_{ij}^k\big)_{m\times n} (k = 1,2,\dots,t; i = 1,2,\dots,m; j = 1,2,\dots,n)$ is obtained from the decision matrix $D^k = \big(A_{ij}^k\big)_{m\times n}$ by the following formula:

$$H_{ij}^k = \frac{1}{2}\alpha\big(1 + T_{ij}^k - F_{ij}^k\big) + \frac{1}{3}(1-\alpha)\big(2 + T_{ij}^k - I_{ij}^k - F_{ij}^k\big) \quad (3)$$

Step 2: Calculate the average matrix

From the obtained hybrid score-accuracy matrices, the average matrix

$H^* = \big(H_{ij}^*\big)_{m\times n} (k = 1,2,\dots,t; i = 1,2,\dots,m, j = 1,2,\dots,n)$ is calculated by $H_{ij}^* = \frac{1}{t}\sum_{k=1}^{t}\big(H_{ij}^k\big)$. (4)

The collective correlation coefficient between $Y^k (k = 1,2,\dots.,t)$ and Y^* represented as follows:

$$e_k = \sum_{i=1}^{m} \frac{\sum_{j=1}^{n} H_{ij}^k H_{ij}^*}{\sqrt{\sum_{j=1}^{n}\big(H_{ij}^k\big)^2}\sqrt{\sum_{j=1}^{n}\big(H_{ij}^*\big)^2}} \quad (5)$$

Step 3: Calculate the weight

The decision makers may have personal opinion and some individuals may give excessively high or excessively low preference values with respect to their favoured or least-liked objects in practical decision-making problems. The opinions are false or biased which will be assigned by very low weights. The average matrix H^* is the maximum conciliation among all individual decisions of the group as the ''mean value'' is the ''distributing centre'' of all elements in a set i.e. if a hybrid score-accuracy matrix H_k is closer to the average one H^* then, the preference value (hybrid score-accuracy value) of the kth decision maker is closer to the average value and the evaluation is more reasonable and more important, thus the weight of the kth decision maker is bigger which can be defined as:

$$\lambda_k = \frac{e_k}{\sum_{k=1}^{t} e_k} \text{ where } 0 \le \lambda_k \le 1, \ \sum_{k=1}^{t} \lambda_k = 1 \text{ for } k = 1,2,\dots,t \quad (6)$$

Step 4: Calculate collective hybrid score-accuracy matrix

For the weight vector $\boldsymbol{\lambda} = (\boldsymbol{\lambda_1}, \boldsymbol{\lambda_2}, \dots, \boldsymbol{\lambda_k})^T$ of decision makers obtained from equation (6), we collect all individual hybrid score-accuracy matrices of $\boldsymbol{H^k = \big(H_{ij}^k\big)_{m\times n} (k = 1,2,\dots,t; i = 1,2,\dots,m; j = 1,2,\dots,n)}$ into a collective hybrid score-accuracy matrix $\boldsymbol{H = \big(H_{ij}\big)_{m\times n}}$ by the following $\boldsymbol{H_{ij} = \sum_{k=1}^{t} \lambda_k H_{ij}^k}$ (7)

Step 5: Weight model for attributes

For a specific decision problem, the weights of the attributes can be given in advance by a partially known subset corresponding to the weight information of the attributes, which is denoted by W. Reasonable weight values of the attributes should make the overall averaging value of all alternatives as large as possible because they can enhance the obvious differences and identification of various alternatives under the attributes to easily rank the alternatives. To determine the weight vector of the attributes Ye introduced the following optimization model:

$$\max W = \frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{n} W_j H_{ij}$$

Subject to,

$$\sum_{j=1}^{n} W_j = 1$$

$$W_j > 0 \qquad (8)$$

In this linear programming problem, weight vector can be easily solved to resolve of the attributes

$$\mathbf{W} = (\mathbf{W_1}, \mathbf{W_2}, \dots, \mathbf{W_n})^{\mathbf{T}}$$

Step 6: Ranking alternatives

To rank alternatives, we can sum all values in each row of the collective hybrid score-accuracy matrix corresponding to the attribute weights by the overall weighted hybrid score-accuracy value of each alternative

$A_i(i = 1,2, \dots, m)$: $M(A_i) = \sum_{j=1}^{n} W_j Y_{ij}$ (9)

According to the overall hybrid score-accuracy values of $\boldsymbol{M(A_i)}$ $(\boldsymbol{i = 1, 2, \dots, m})$, we can rank alternatives $(\boldsymbol{A_i})$ $(\boldsymbol{i = 1, 2, \dots, m})$ in descending order and choose the best one.

4. Using to analyze the prformances of feedback on faculty teaching using hybrid score accuracy function

In recent years feedback system is very essential for many institutes. The feedback students provide about their teaching on their end of semester course evaluation can be valuable in helping them to improve and improve their teaching. This system can help us to improve the teacher's performance skill, techniques, teaching style. Feedback system contains various factor like "Timeliness", "Communication skill", "Control of the class". In our problem,we assume five faculty (i.e. alternatives) F_1, F_2, F_3, F_4, F_5 have been chosen and evaluated by the form of SVNNs under the below factors on the fuzzy concept "excellence" and select the best faculty by ranking them. Also we assume a group of four students or experts,S_1, S_2, S_3, S_4, S_5 give the result of the performance of feedback of teachers. Factors relating with feedback system are as follows:

C_1 → Timeliness
C_2 → Attempt to complete syllabus & adherence to lecture plan
C_3 →Whether well performed & enough knowledgeable about the topic
C_4 → Communication skill
C_5 → Control of the class
C_6 → Involvement in doubt clearance
C_7 → Present the material clearly in the class
C_8 → Regular checking of class assignments
C_9 →proper experimental guidance
C_{10} → Responsibility
C_{11} → Teacher is approachable outside the class
C_{12} → Assessment as a guide and well wisher

Table 1: Single valued neutrosophic decision matrix S_1

Alter.	**Factor**											
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
F_1	0.8, ⟨0.1,⟩ 0.0	0.8, ⟨0.2.⟩ 0.1	0.8, ⟨0.1,⟩ 0.1	0.7, ⟨0.2,⟩ 0.1	0.7, ⟨0.2.⟩ 0.1	0.8, ⟨0.2,⟩ 0.2	0.7, ⟨0.2,⟩ 0.1	0.8, ⟨0.2,⟩ 0.1	0.8, ⟨0.1,⟩ 0.0	0.7, ⟨0.2,⟩ 0.1	0.7, ⟨0.2,⟩ 0.0	0.7 ⟨0. 0.
F_2	0.7, ⟨0.1,⟩ 0.1	0.8, ⟨0.2,⟩ 0.3	0.8, ⟨0.0,⟩ 0.2	0.8, ⟨0.2,⟩ 0.1	0.7, ⟨0.1,⟩ 0.1	0.7, ⟨0.2,⟩ 0.3	0.8, ⟨0.1,⟩ 0.1	0.8, ⟨0.3,⟩ 0.3	0.7, ⟨0.1,⟩ 0.1	0.8, ⟨0.2,⟩ 0.2	0.8, ⟨0.1,⟩ 0.2	0.8 ⟨0. 0.
F_3	0.8, ⟨0.1,⟩ 0.1	0.8, ⟨0.3,⟩ 0.3	0.8, ⟨0.1,⟩ 0.2	0.8, ⟨0.2,⟩ 0.2	0.7, ⟨0.1,⟩ 0.2	0.8, ⟨0.2,⟩ 0.3	0.8, ⟨0.1,⟩ 0.1	0.6, ⟨0.3,⟩ 0.3	0.7, ⟨0.1,⟩ 0.1	0.8, ⟨0.1,⟩ 0.2	0.8, ⟨0.1,⟩ 0.1	0.8 ⟨0. 0.
F_4	0.7, ⟨0.1,⟩ 0.1	0.8, ⟨0.2,⟩ 0.0	0.8, ⟨0.1,⟩ 0.3	0.8, ⟨0.2,⟩ 0.2	0.8, ⟨0.2,⟩ 0.3	0.7, ⟨0.2,⟩ 0.2	0.7, ⟨0.3,⟩ 0.3	0.7, ⟨0.1,⟩ 0.2	0.7, ⟨0.3,⟩ 0.3	0.8, ⟨0.1,⟩ 0.2	0.7, ⟨0.3,⟩ 0.0	0.7 ⟨0. 0.
F_5	0.8, ⟨0.2,⟩ 0.0	0.8, ⟨0.1.⟩ 0.1	0.8, ⟨0.3,⟩ 0.1	0.7, ⟨0.2,⟩ 0.3	0.6, ⟨0.4,⟩ 0.4	0.8, ⟨0.4,⟩ 0.2	0.7, ⟨0.3,⟩ 0.1	0.7, ⟨0.4,⟩ 0.1	0.8, ⟨0.3,⟩ 0.0	0.7, ⟨0.2,⟩ 0.4	0.7, ⟨0.2,⟩ 0.3	0.7 ⟨0. 0.

Table 2: Single valued neutrosophic decision matrix S_2

Alter.	**Factor**											
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
F_1	0.8, ⟨0.2,⟩ 0.0	0.8, ⟨0.1.⟩ 0.1	0.8, ⟨0.3,⟩ 0.1	0.7, ⟨0.2,⟩ 0.3	0.7, ⟨0.2,⟩ 0.2	0.8, ⟨0.1,⟩ 0.2	0.7, ⟨0.3,⟩ 0.1	0.7, ⟨0.2,⟩ 0.1	0.8, ⟨0.3,⟩ 0.0	0.6, ⟨0.2,⟩ 0.2	0.7 ⟨0. 0.	0.7, ⟨0.2,⟩ 0.2
F_2	0.7, ⟨0.1,⟩ 0.1	0.8, ⟨0.2,⟩ 0.3	0.8, ⟨0.3,⟩ 0.2	0.8, ⟨0.2,⟩ 0.1	0.8, ⟨0.1,⟩ 0.1	0.7, ⟨0.2,⟩ 0.2	0.8, ⟨0.1,⟩ 0.1	0.8, ⟨0.1,⟩ 0.3	0.7, ⟨0.1,⟩ 0.1	0.8, ⟨0.2,⟩ 0.0	0.8 ⟨0. 0.	0.8, ⟨0.1,⟩ 0.3
F_3	0.8, ⟨0.1,⟩ 0.0	0.8, ⟨0.1,⟩ 0.3	0.8, ⟨0.1,⟩ 0.1	0.8, ⟨0.2,⟩ 0.2	0.7, ⟨0.1,⟩ 0.2	0.8, ⟨0.1⟩ 0.3	0.8, ⟨0.2,⟩ 0.2	0.6, ⟨0.3,⟩ 0.2	0.7, ⟨0.3,⟩ 0.1	0.7, ⟨0.1,⟩ 0.3	0.8 ⟨0. 0.	0.8, ⟨0.2,⟩ 0.1
F_4	0.7, ⟨0.1,⟩ 0.1	0.8, ⟨0.2,⟩ 0.3	0.8, ⟨0.1,⟩ 0.3	0.8, ⟨0.2,⟩ 0.2	0.8, ⟨0.3,⟩ 0.3	0.7, ⟨0.3,⟩ 0.2	0.7, ⟨0.3,⟩ 0.3	0.8, ⟨0.1,⟩ 0.2	0.7, ⟨0.3,⟩ 0.3	0.8, ⟨0.3,⟩ 0.0	0.7 ⟨0. 0.	0.7, ⟨0.2,⟩ 0.1
F_5	0.8, ⟨0.2,⟩ 0.4	0.8, ⟨0.1,⟩ 0.4	0.8, ⟨0.3,⟩ 0.2	0.7, ⟨0.4,⟩ 0.3	0.6, ⟨0.4,⟩ 0.1	0.8, ⟨0.4,⟩ 0.3	0.7, ⟨0.3,⟩ 0.1	0.7, ⟨0.3,⟩ 0.1	0.8, ⟨0.3,⟩ 0.4	0.7, ⟨0.2,⟩ 0.4	0.7 ⟨0. 0.	0.7, ⟨0.2,⟩ 0.4

Table 3: Single valued neutrosophic decision matrix S_3

Alter.	**Factor**											
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
F_1	0.8, ⟨0.3,⟩ 0.1	0.8, ⟨0.2,⟩ 0.1	0.8, ⟨0.2,⟩ 0.1	0.7, ⟨0.2,⟩ 0.2	0.7, ⟨0.2,⟩ 0.0	0.8, ⟨0.2,⟩ 0.2	0.6, ⟨0.3,⟩ 0.1	0.7, ⟨0.2,⟩ 0.3	0.8, ⟨0.3,⟩ 0.1	0.6, ⟨0.2,⟩ 0.3	0.7 ⟨0. 0.	0.7, ⟨0.2,⟩ 0.0
F_2	0.7, ⟨0.1,⟩ 0.2	0.8, ⟨0.2,⟩ 0.2	0.8, ⟨0.3,⟩ 0.0	0.8, ⟨0.2,⟩ 0.3	0.8, ⟨0.2,⟩ 0.1	0.7, ⟨0.2,⟩ 0.2	0.6, ⟨0.1,⟩ 0.1	0.8, ⟨0.1,⟩ 0.3	0.7, ⟨0.2,⟩ 0.2	0.8, ⟨0.2,⟩ 0.2	0.8 ⟨0. 0.	0.8, ⟨0.1,⟩ 0.3
F_3	0.8, ⟨0.2.⟩ 0.1	0.8, ⟨0.2,⟩ 0.3	0.8, ⟨0.1,⟩ 0.2	0.8, ⟨0.1,⟩ 0.2	0.7, ⟨0.2,⟩ 0.3	0.8, ⟨0.2,⟩ 0.1	0.8, ⟨0.3,⟩ 0.1	0.6, ⟨0.3,⟩ 0.3	0.7, ⟨0.1,⟩ 0.3	0.7, ⟨0.1,⟩ 0.2	0.8 ⟨0. 0.	0.8, ⟨0.1,⟩ 0.1
F_4	0.7, ⟨0.1,⟩ 0.1	0.8, ⟨0.2,⟩ 0.3	0.8, ⟨0.4,⟩ 0.3	0.8, ⟨0.4,⟩ 0.2	0.8, ⟨0.3,⟩ 0.3	0.7, ⟨0.3,⟩ 0.2	0.7, ⟨0.4,⟩ 0.3	0.8, ⟨0.1,⟩ 0.2	0.7, ⟨0.3,⟩ 0.3	0.8, ⟨0.4,⟩ 0.0	0.7 ⟨0. 0.	0.7, ⟨0.2,⟩ 0.4
F_5	0.8, ⟨0.2,⟩ 0.4	0.8, ⟨0.1,⟩ 0.4	0.8, ⟨0.3,⟩ 0.2	0.8, ⟨0.4,⟩ 0.3	0.7, ⟨0.4,⟩ 0.2	0.8, ⟨0.4,⟩ 0.1	0.7, ⟨0.3,⟩ 0.1	0.7, ⟨0.3,⟩ 0.2	0.8, ⟨0.3,⟩ 0.3	0.6, ⟨0.2,⟩ 0.4	0.7 ⟨0. 0.	0.7, ⟨0.4,⟩ 0.4

Table 4: Single valued neutrosophic decision matrix S_4

Alter.	**Factor**											
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
F_1	0.8, ⟨0.3, 0.1	0.8, ⟨0.2, 0.0	0.8, ⟨0.3, 0.1	0.8, ⟨0.2, 0.2	0.7, ⟨0.2, 0.1	0.8, ⟨0.2, 0.3	0.7, ⟨0.3, 0.3	0.7, ⟨0.2, 0.2	0.8, ⟨0.3, 0.2	0.7, ⟨0.2, 0.3	0.7, ⟨0.2, 0.2	0.7, ⟨0.2,⟩ 0.2
F_2	0.7, ⟨0.1, 0.3	0.8, ⟨0.2, 0.3	0.8, ⟨0.3, 0.3	0.8, ⟨0.2, 0.3	0.8, ⟨0.2, 0.2	0.7, ⟨0.2, 0.1	0.6, ⟨0.3, 0.1	0.8, ⟨0.1, 0.3	0.7, ⟨0.3, 0.2	0.8, ⟨0.2, 0.2	0.8, ⟨0.3, 0.0	0.8, ⟨0.2,⟩ 0.3
F_3	0.8, ⟨0.2, 0.1	0.8, ⟨0.3, 0.0	0.8, ⟨0.1, 0.2	0.8, ⟨0.2, 0.2	0.7, ⟨0.1, 0.1	0.8, ⟨0.2, 0.2	0.8, ⟨0.1, 0.1	0.7, ⟨0.3, 0.3	0.7, ⟨0.1, 0.0	0.8, ⟨0.1, 0.2	0.8, ⟨0.2, 0.1	0.8, ⟨0.1,⟩ 0.0
F_4	0.7, ⟨0.1, 0.3	0.8, ⟨0.2, 0.3	0.8, ⟨0.3, 0.1	0.8, ⟨0.2, 0.2	0.8, ⟨0.2, 0.3	0.7, ⟨0.2, 0.3	0.7, ⟨0.1, 0.0	0.7, ⟨0.1, 0.3	0.7, ⟨0.2, 0.2	0.8, ⟨0.2, 0.2	0.7, ⟨0.3, 0.2	0.7, ⟨0.1,⟩ 0.3
F_5	0.8, ⟨0.1, 0.4	0.8, ⟨0.1, 0.4	0.8, ⟨0.3, 0.3	0.8, ⟨0.4, 0.3	0.7, ⟨0.4, 0.4	0.8, ⟨0.4, 0.1	0.7, ⟨0.3, 0.3	0.7, ⟨0.4, 0.2	0.8, ⟨0.3, 0.3	0.6, ⟨0.3, 0.4	0.7, ⟨0.3, 0.3	0.7, ⟨0.4,⟩ 0.4

able 5: Single valued neutrosophic decision matrix S_5

Alter.	Factor											
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
F_1	0.8, ⟨0.3,⟩ 0.2	0.8, ⟨0.2,⟩ 0.3	0.8, ⟨0.3,⟩ 0.0	0.8, ⟨0.2,⟩ 0.1	0.7, ⟨0.2,⟩ 0.0	0.8, ⟨0.2,⟩ 0.2	0.7, ⟨0.3,⟩ 0.0	0.7, ⟨0.2,⟩ 0.1	0.8, ⟨0.3,⟩ 0.2	0.7, ⟨0.2,⟩ 0.3	0. ⟨0. 0.	0.7, ⟨0.2,⟩ 0.3
F_2	0.7, ⟨0.3,⟩ 0.2	0.8, ⟨0.2,⟩ 0.2	0.8, ⟨0.3,⟩ 0.3	0.8, ⟨0.2,⟩ 0.3	0.8, ⟨0.3,⟩ 0.2	0.7, ⟨0.2,⟩ 0.2	0.6, ⟨0.1,⟩ 0.3	0.8, ⟨0.1,⟩ 0.3	0.7, ⟨0.2,⟩ 0.3	0.8, ⟨0.2,⟩ 0.2	0. ⟨0. 0.	0.8, ⟨0.3,⟩ 0.3
F_3	0.8, ⟨0.1.⟩ 0.1	0.8, ⟨0.3,⟩ 0.3	0.8, ⟨0.1,⟩ 0.1	0.8, ⟨0.2,⟩ 0.2	0.7, ⟨0.1,⟩ 0.2	0.8, ⟨0.2,⟩ 0.2	0.8, ⟨0.1,⟩ 0.1	0.6, ⟨0.3,⟩ 0.0	0.7, ⟨0.1,⟩ 0.1	0.8, ⟨0.1,⟩ 0.2	0. ⟨0. 0.	0.8, ⟨0.1,⟩ 0.2
F_4	0.7, ⟨0.1,⟩ 0.1	0.8, ⟨0.2,⟩ 0.0	0.8, ⟨0.3,⟩ 0.3	0.8, ⟨0.2,⟩ 0.1	0.8, ⟨0.2,⟩ 0.3	0.7, ⟨0.2,⟩ 0.3	0.7, ⟨0.1,⟩ 0.3	0.7, ⟨0.1,⟩ 0.3	0.7, ⟨0.2,⟩ 0.3	0.8, ⟨0.1,⟩ 0.3	0. ⟨0. 0.	0.7, ⟨0.2,⟩ 0.3
F_5	0.8, ⟨0.1,⟩ 0.4	0.8, ⟨0.1,⟩ 0.4	0.8, ⟨0.3,⟩ 0.4	0.8, ⟨0.4,⟩ 0.3	0.7, ⟨0.2,⟩ 0.4	0.8, ⟨0.4,⟩ 0.2	0.8, ⟨0.3,⟩ 0.3	0.7, ⟨0.4,⟩ 0.2	0.8, ⟨0.3,⟩ 0.1	0.6, ⟨0.3,⟩ 0.1	0. ⟨0. 0.	0.7, ⟨0.4,⟩ 0.4

using equation(3) we obtained hybrid score accuracy for the four decision matrices using $\alpha = 0.5$

Table 6: Hybrid score accuracy matrix S_1

Alter.	Factor											
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
F_1	0.9	0. 8417	0. 8583	0.8	0.8	0.8	0.8	0. 8417	0.9	0.8	0 .8417	0.8
F_2	0. 8167	0. 7583	0. 8333	0. 8417	0. 8167	0. 7167	0. 8583	0. 7417	0. 8167	0.8	0. 8167	0. 775
F_3	0. 8583	0 .7417	0. 8167	0.8	0.775	0. 7583	0. 8583	0. 6583	0. 8167	0. 8167	0. 8583	0.9
F_4	0. 8167	0. 8833	0. 775	0.8	0. 7583	0. 7583	0.7	0. 775	0.7	0. 8167	0. 825	0.8
F_5	0. 8833	0. 8583	0. 6583	0. 7167	0.6	0.6	0. 7833	0. 7667	0. 8167	0. 675	0. 7167	0. 675

Table 7: Hybrid score accuracy matrix S_2

Alter.	Factor											
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
F_1	0. 883	0. 858	0.82	0. 716	0. 758	0. 816	0. 783	0. 466	0. 866	0. 7167	0. 716	0. 758
F_2	0. 816	0. 758	0. 7833	0. 841	0. 858	0. 758	0. 858	0. 775	0. 816	0. 7167	0. 783	0. 775
F_3	0. 733	0. 775	0. 8583	0.8	0. 775	0. 775	0.8	0.7	0. 783	0. 7333	0. 841	0. 841
F_4	0. 816	0. 758	0. 775	0.8	0. 741	0. 741	0.7	0. 816	0.7	0.866	0. 783	0. 466
F_5	0. 716	0. 733	0. 7833	0. 683	0. 725	0. 725	0. 783	0. 783	0.7	0. 675	0.8	0. 675

Table 8: Hybrid score accuracy matrix S_3

Alter.	Factor											
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
F_1	0. 825	0. 841	0. 8417	0. 758	0. 508	0.8	0. 741	0. 7167	0. 825	0. 675	0.8	0. 5083
F_2	0. 775	0.8	0. 8667	0. 758	0. 841	0. 758	0. 775	0.77	0. 758	0.8	0. 783	0.77
F_3	0. 8417	0. 758	0. 8167	0. 816	0. 716	0. 841	0. 825	0. 6583	0. 733	0. 775	0. 841	0. 8583
F_4	0. 8167	0. 758	0.72	0. 766	0. 741	0. 741	0. 683	0. 8166	0. 733	0. 85	0. 783	0. 675
F_5	0.71	0. 733 3	0. 7833	0. 725	0. 725	0. 808	0. 783	0. 7417	0. 741	0.633	0. 716	0. 6417

Table 9: Hybrid score accuracy matrix S_4

Alter.	Factor											
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
F_1	0. 825	0. 883	0. 825	0.8	0.8	0. 758	0.7	0. 758	0. 7833	0. 716	0. 7583	0. 758
F_2	0. 733	0. 758	0. 7417	0. 758	0.8	0.8	0. 741	0.77	0. 7417	0.8	0. 7583	0. 758
F_3	0. 841	0. 866	0. 8167	0.8	0. 816	0.8	0. 858	0.7	0. 8583	0. 816	0. 8417	0.9
F_4	0. 733	0. 758	0. 825	0.8	0. 758	0. 716	0. 858	0. 733	0. 7583	0.8	0.741	0. 733
F_5	0. 733	0. 733	0.7417	0. 958	0. 641	0. 808	0.7	0. 725	0. 74741	0. 616	0. 7333	0. 741

Table 10: Hybrid score accuracy matrix S_5

Alter.	Factor											
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
F_1	0. 783	0. 758	0. 841	0. 841	0.7	0.8	0. 825	0.8	0. 783	0. 716	0. 758	0. 7167
F_2	0. 741	0.8	0. 741	0. 758	0. 783	0. 758	0. 691	0. 775	0. 716	0.8	0. 783	0. 7417
F_3	0. 858	0. 7417	0. 858	0.8	0. 775	0.8	0. 858	0. 783	0. 816	0. 816	0. 858	0. 8167
F_4	0. 816	0. 883	0. 741	0. 841	0. 758	0. 716	0. 733	0. 733	0. 716	0. 775	0.7	0. 7167
F_5	0. 733	0. 733	0.7	0. 725	0. 675	0. 766	0. 725	0. 725	0 .825	0. 741	0. 741	0 .641

and by using equation (4) we can find out the average matrix H* from the above hybrid score-accuracy matrices,

Table 10: Average matrix H^*

Alter.	Factor											
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
F_1	0.84 332	0.83 666	0.84 232	0.78 334	0.71 332	0.79 5	0.77	0.71 668	0.83 166	0.72 502	0.77 5	0.70 832
F_2	0.77 668	0.77 498	0.79 334	0.79 166	0.82	0.75 832	0.78 4	0.76 834	0.77 002	0.78 334	0.80 666	0.76 5
F_3	0.82 66	0.77 668	0.83 334	0.80 332	0.77 168	0.79 5	0.83 898	0.69 998	0.80 166	0.79 168	0.84 834	0.86 334
F_4	0.80 002	0.80 83	0.76 834	0.80 168	0.75 166	0.73 502	0.73 498	0.77 498	0.72 166	0.82 168	0.76 666	0.67 834
F_5	0.75 652	0.75 83	0.73 332	0.76 166	0.67 334	0.77 5	0.75 498	0.74 834	0.76 502	0.66 834	0.74 168	0.65 502

From the equations. (5) and (6), we determine the weights of the three decision makers as follows: $\lambda_1 = 0.200064, \lambda_2 = 0.199827, \lambda_3 = 0.200016, \lambda_4 = 0.199978, \lambda_5 = 0.200115$
Hence, the hybrid score-accuracy values of the different decision makers' evaluations are aggregated[48] by equation (7) and the information about attribute weights is incompletely known weight vectors where, $w = 0.08 \leq w_i \leq 0.09\ \forall i = 1,2,\dots,12$. By using the linear programming model (8), we obtain the weight vector of the attributes as: $w = \begin{bmatrix} 0.076,0.082,0.078,0.084,0.089,0.081, \\ 0.0760.080,0.076,0.092,0.095,0.091 \end{bmatrix}^T$.
By applying equation (9), we can calculate the overall hybrid score-accuracy values $M(A_i) \forall i = 1,2,\dots,5$
$M(A_1) = 0.792062, M(A_2) = 0.763079,\ M(A_3) = 0.759433, M(A_4) = 0.775559, M(A_5) = 0.767938$.

According to the above values of $\boldsymbol{M(A_i)}$ the ranking order of the alternatives is $\boldsymbol{A_1 > A_4 > A_5 > A_2 > A_3}$. So faculty1 shows their best performance during a session

5. Conclusion

In this paper, we employ the score and accuracy functions, hybrid score-accuracy functions of SVNNs to find out the teacher's performance by feedback system using single valued neutrosophic environments, where the weights of decision makers are completely unknown and the weights of attributes are incompletely known.
Here, the weight values obtained from the models mainly decrease the effect of some unreasonable evaluations, e.g. the decision makers may have personal opinion and some individuals

may give excessively high or excessively low preference values with respect to their favoured or least-liked objects in practical decision-making problems. Then we calculate the collective hybrid score-accuracy matrix and weight model for each attributes to rank them and select the best faculty.Therefore, decision-making methods offer simple calculations and good flexibility. The advantage of this model is to help us for handling with the group decision-making problems with unknown weights by comparisons with other relative decision-making methods under single valued neutrosophic environments. In future we shall focusing in the extension of the methods and other application such as pattern recognition, swarm optimization and so on.

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