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Multi-criteria Group Decision Making Approach for Teacher Recruitment in Higher Education under Simplified Neutrosophic Environment

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Abstract

Teacher recruitment is a multi-criteria group decision-making process involving subjectivity, imprecision, and fuzziness that can be suitably represented by neutrosophic sets. Neutrosophic set, a generalization of fuzzy sets is characterized by a truth-membership function, falsity-membership function and an indeterminacy-membership function. These functions are real standard or non-standard subsets of] 0^-, 1^+[.There is no restriction on the sum of the functions, so the sum lies between]0^-, 3^+[. A neutrosophic approach is a more general and suitable way to deal with imprecise information, when compared to a fuzzy set. The purpose of this study is to develop a neutrosophic multi-criteria group decision-making model based on hybrid score-accuracy functions for teacher recruitment in higher education. Eight criteria obtained from expert opinions are considered for recruitment process. The criteria are namely academic performance index, teaching aptitude, subject knowledge, research experience, leadership quality, personality, management capacity, and personal values. In this paper we use the score and accuracy functions and the hybrid score-accuracy functions of single valued neutrosophic numbers (SVNNs) and ranking method for SVNNs. Then, multi-criteria group decision-making method with unknown weights for attributes and incompletely known weights for decision makers is used based on the hybrid score-accuracy functions under single valued neutrosophic environments. We use weight model for attributes based on the hybrid score-accuracy functions to derive the weights of decision makers and attributes from the decision matrices represented by the form of SVNNs to decrease the effect of some unreasonable evaluations. Moreover, we use the overall evaluation formulae of the weighted hybrid score-accuracy functions for each alternative to rank the alternatives and recruit the most desirable teachers. Finally, an educational problem for teacher selection is provided to illustrate the effectiveness of the proposed model.

Keywords: Multi-criteria group decision- making, Hybrid score-accuracy function, Neutrosophic numbers (SVNNs), and Single valued Neutrosophic set, Teacher recruitment

Introduction

Teacher recruitment problem can be considered as a multi-criteria group decision-making (MCGDM) problem that generally consists of selecting the most desirable alternative from all the feasible alternatives. Classical MCGDM approaches [1,2,3] deal with crisp numbers i.e. the ratings and the weights of criteria are measured by crisp numbers. However, it is not always possible to present the information by crisp numbers. In order to deal this sutuation fuzzy sets introduced by Zadeh in 1965 [4] can be used. Atanassov [5]extended the concept of fuzzy sets to intuitionistic fuzzy sets(IFSs) in 1986. Fuzzy and intuitionistic MCGDM appraoches [6,7] were studied with fuzzy or intuitionistic fuzzy numbers i.e. the ratings and the weights are expressed by linguistic variables characterized by fuzzy or intuitionistic fuzzy numbers.

Teacher recruitment process for higher education can be considered as a spcial case of personnel selection. The traditional methods for recruiting teahers generally involve subjective judgment of experts, which make the accuracy of the results highly questionable. In order to tackle the problem, new methodology is urgently needed. Liang and Wang [8] studied fuzzy multi-criteria decision making (MCDM) algorithm for personnel selection. Karsak [9] presented fuzzy MCDM approach based on ideal and anti-ideal solutions for the selection of the most suitable candidate. Günör et al.[10] developed analytical hierarchy process (AHP) for personnel selection. Dağdeviren [11] studied a hybrid model based on analytical network process (ANP) and modified technique for order preference by similarity to ideal solution (TOPSIS)[12] for supporting the personnel selection process in the manufacturing systems. Dursun and Karsak [13] discussed fuzzy MCDM approach by using TOPSIS with 2-tuples for personnel selection. Personnel selection studies were well reviewed by Robertson and Smith [14]. In their studies, Robertson and Smith [14] investigated the role of job analysis, contemporary models of work performance, and set of criteria employed in personnel selection process. Ehrgott and Gandibleux [15] presented a comprehensive survey of the state of the art in MCDM. Pramanik and Mukhopadhay [16] presented a intuitionistic fuzzy MCDM approach for teacher selection based grey relational analysis.

Though fuzzy and intuitionistic fuzzy MCDM problems are widely studied, but indeterminacy should be incorportated in the model formulation of the problems. Inderterminacy plays an important role in decision making process. So neutrosophic set [17] generalization of intuitionistic fuzzy sets should be incorporated in the decision making process. Neutrosophic set was introduced to represent mathematical model of uncertainty, imprecision, and inconsistency. Biswas et al. [18] presented entropy based grey relational analysis method for multi-attribute decision-making under single valued neutrosopic assesment. Biswas et al.[19] also studied a new methodology to deal neutrosophic multi-attribute decision-making problem. Ye [20] proposed the correlation coefficient of SVNSs for single valued neutrosophic multi-critera decision-making problems.

The ranking order of alternatives plays an important role in decision-making process. In this study, we present a multi-criteria group decision-making approach for teacher recritment in higher education with unknown weights based on score and accuracy functions, hybrid score-accuracy functions proposed by J. Ye [21] under simplified neutrosophic environment.

Rest of the paper is organized in the following way. Section II presents preliminaries of neutrosophic sets and Section III presents operational definitions. Section IV presents methodology based on hybrid score-accuracy functions Section V is devoted to present an example of teacher selection in higher education based on hybrid score-accuracy functions . Section VI presents conclusion, finally, section VII presents the concluding remarks.

Section II

Mathematical preliminaries on Neutrosophic set

Some basic concepts of SNSs:

The neutrosophic set is a part of neutrosophy and generalizes fuzzy set, IFS, and IVIFS from philosophical point of view [22].

Definition1. Neutrosophic set [22]

Let X be a space of points (objects), with a generic element in X denoted by x. A neutrosophic set 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 or nonstandard subsets of $]0, 1[$, i.e.,$T_A(x): X \to]0^-, 1^+[$,
$I_A(x): X \to]0^-, 1^+[$, and $F_A(x): X \to]0^-, 1^+[$. Hence, there is no restriction on the sum of $T_A(x)$, $I_A(x)$ and $F_A(x)$ and $0^- \le \sup T_A(x) + \sup I_A(x) + \sup F_A(x) \le 3^+$.

Definition 2. Single valued neutrosophic sets [23].

Let X be a space of points (objects), with a generic element in X denoted by x. A neutrosophic set 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 $F_A(x)$. If the functions $T_A(x)$, $I_A(x)$ and $F_A(x)$ are singleton subintervals/subsets in the real standard [0, 1], that is$T_A(x): X \to [0, 1]$, $I_A(x): X \to [0, 1]$, and $F_A(x): X \to [0, 1]$. Then, a simplification of the neutrosophic set A is denoted by $A = \{\langle x, T_A(x), I_A(x), F_A(x)\rangle / x \in X\}$ which is called a SNS. It is a subclass of a neutrosophic set and includes SVNS and INS. In this paper, we shall use the SNS whose values of the functions $T_A(x)$, $I_A(x)$ and $F_A(x)$ can be described by three real numbers (i.e. a SVNS) in the real standard [0, 1].

Definition 3. Single valued neutrosophic number (SNN) [21]

Let X be a universal set. 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 $F_A(x)$. Then, a SVNS A can be denoted by the following symbol: $A = \{\langle x, T_A(x), I_A(x), F_A(x)\rangle / x \in X\}$, where $T_A(x)$, $I_A(x)$, $F_A(x) \in [0, 1]$ for each point x in X. Therefore, the sum of $T_A(x)$, $I_A(x)$ and $F_A(x)$ satisfies the condition $0 \le T_A(x) + I_A(x) + F_A(x) \le 3$. For a SVNS A in X, the triple $\langle T_A(x), I_A(x), F_A(x)\rangle$ is called single valued neutrosophic number (SVNN), which is the fundamental element of a SVNS.

Definition 4. Complement of SVNS [21]

The complement of a SVNS A is denoted by A^c and defined as $T_A^c(x) = F_A(x)$, $I_A^c(x) = 1 – I_A(x)$,
$F_A^c(x) = T_A(x)$ for any x in X. Then, it can be denoted by the following form:

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

For two SVNSs A and B in X, two of their relations are defined as follows: A SVNS A is contained in the other SVNS B, $A \subseteq B$, if and only if $T_A(x) \le T_B(x)$, $I_A(x) \ge I_B(x)$, $F_A(x) \ge F_B(x)$ for any x in X.

Two SVNSs A and B are equal, written as A= B, if and only if $A \subseteq B$ and $B \subseteq A$.

Ranking methods for SVNNs

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

Definition 5 Score function and accuracy function [21]

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

$s(a) = (1 + T(a) - F(a))/2$ for $s(a) \in [0, 1]$ (1)

$h(a) = (2 + T(a) - F(a) - I(a))/3$ for $h(a) \in [0, 1]$ (2)

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

Theorem 1.

For any two SVNNs a_1 and a_2, if $a_1 > a_2$, then $s(a_1) > s(a_2)$.

Theorem 2.

For any two SVNNs a_1 and a_2, if $s(a_1) = s(a_2)$ and $a_1 \ge a2$, then $h(a_1) \ge h(a_2)$.

For proof, see [21]

Based on theorems 1 and 2, a ranking method between SVNNs can be given by the following definition.

Definition [21]

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

(1) If $s(a_1) > s(a_2)$, then $a_1 > a_2$;
(2) If $s(a_1) = s(a_2)$ and $h(a_1) \ge h(a_2)$, then $a_1 \ge a_2$;

Section III

Operational definitions of the terms stated in the problem

i) Academic performance: Academic performance implies the percentage of marks (if grades are given, transform it into marks) obtained in post graduate examinations.

ii) Teaching aptitude: Degree of knowledge in strategies of instruction and information communication technology (ICT).

iii) Subject knowledge: Degree of knowledge of a person in his/her respective field of study to be delivered during his/her instruction.

iv) Research experience: Research experience of a person implies his or her contribution of new knowledge in the form of publication in reputed peer reviewed journals with ISSN.

v) Leadership quality: Leadership quality of a person implies the ability a) to challenge status quo b) to implement rational decision

vi) Personality: Defining and explaining personality are of prime importance while recruiting teachers. But how do psychologists measure and study personality? Four distinct methods are most common, namely behavioral observation, interviewing, projective tests, and questionnaires. McCrae & Costa [24] studied five-factor model of personality. Five factors of personality are extraversion versus introversion, agreeableness versus antagonism, conscientiousness versus undirectedness, neuroticism versus emotional stability, and openness versus not openness. In this study personality implies the five factors of personality traits of five factor model.

vii) Management capacity: Management capacity of a person implies his/her ability to manage in the actual teaching learning process.

viii) Values: Values will implicitly refer to personal values that serve as guiding principles about how individuals ought to behave.

Section IV

Multi-criteria group decision-making methods based on hybrid score-accuracy functions

In a multi-criteria group decision-making problem, let A= $\{A_1, A_2, \ldots, A_m\}$ be a set of alternatives and let C= $\{C_1, C_2, \ldots, C_n\}$ be a set of attributes. Then, the weights of decision makers and attributes are not assigned previously, where the information about the weights of the decision makers is completely unknown and the information about the weights of the attributes is incompletely known in the group decision-making problem. In such a case, we develop two methods 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.

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, …, m) on the attribute C_j (j= 1, 2, …, n), which is represented by the form of a SVNS:

$$A_i^k = \left\{ \left\langle C_j, T_{A_i}^k(C_j), I_{A_i}^k(C_j), F_{A_i}^k(C_j) \right\rangle / C_j \in C \right\}$$

Here, $0 \leq T_{A_i}^k(C_j) + I_{A_i}^k(C_j) + F_{A_i}^k(C_j) \leq 3$,

$T_{A_i}^k(C_j) \in [0,1]$, $I_{A_i}^k(C_j) \in [0,1]$, $F_{A_i}^k(C_j) \in [0,1]$,

for k = 1, 2, …., t, j=1, 2, …., n, i=1, 2, ….,m

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

Step1:

Calculate hybrid score-accuracy matrix

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

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

Step2:

Calculatethe average matrix

From the obtained hybrid score-accuracy matrices, the average matrix $Y^* = (Y_{ij}^*)_{m\times n}$ (k= 1, 2, …, t; i= 1, 2, …, m; j= 1, 2, …, n) is calculated by $Y_{ij}^* = \frac{1}{t}\sum_{k=1}^{t}(Y_{ij}^k)$ (4)

The collective correlation coefficient between Y^k (k= 1, 2, …, t) and Y^* represents as follows:

$$e_k = \sum_{i=1}^{m} \frac{\sum_{j=1}^{n} Y_{ij}^k Y_{ij}^*}{\sqrt{\sum_{j=1}^{n}(Y_{ij}^k)^2}\sqrt{\sum_{j=1}^{n}(Y_{ij}^*)^2}}. \qquad (5)$$

Step3:

Determination decision maker's weights

In practical decision-making problems, the decision makers may have personal biases and some individuals may give unduly high or unduly low preference values with respect to their preferred or repugnant objects. In this case, we will assign very low weights to these false or biased opinions. Since the ‘‘mean value’’ is the ‘‘distributing center’’ of all elements in a set, the average matrix Y^* is the maximum compromise among all individual decisions of the group. In mean sense, a hybrid score-accuracy matrix Y^k is closer to the average one Y^*. Then, the preference value (hybrid score-accuracy value) of the k-th decision maker is closer to the average value and his/her evaluation is more reasonable and more important, thus the weight of the k-th decision maker is bigger. Hence, a weight model for decision makers can be defined as:

$$\lambda_k = \frac{e_k}{\sum_{k=1}^{t} e_k} \qquad (6)$$

Where $0 \leq \lambda_k \leq 1$, $\sum_{k=1}^{t}\lambda_k = 1$ for k=1, 2, ….,t.

Step4:

Calculate collective hybrid score-accuracy matrix

For the weight vector $\lambda = (\lambda_1, \lambda_2, \cdots, \lambda_k)^T$ of decision makers obtained from eqation.(6), we accumulate all individual hybrid score-accuracy matrices of $Y^k = (Y_{ij}^k)_{m\times n}$ (k= 1, 2, …, t; i= 1, 2, …, m; j= 1, 2, …, n) into a collective hybrid score-accuracy matrix $Y = (Y_{ij})_{m\times n}$ by the following formula:

$$Y_{ij} = \sum_{k=1}^{t}\lambda_k Y_{ij}^k \qquad (7)$$

Step5:

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:

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

Subject to,

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

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

This is a linear programming problem, which can be easily solved to determine the weight vector of the attributes $W = (W_1, W_2, \ldots, W_n)^T$

Step6:

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, …, m):

$$M(A_i) = \sum_{j=1}^{n} W_j Y_{ij} \qquad (9)$$

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

Step7: End

Section V

Example of Teacher Recruitment Process

Suppose that a university is going to recruit in the post of an assistant professor for a particular subject.. After initial screening, five candidates (i.e. alternatives) A_1, A_2, A_3, A_4, A_5 remain for further evaluation. A committee of four decision makers or experts, D_1, D_2, D_3, D_4 has been formed to conduct the interview and select the most appropriate candidate. Eight criteria obtained from expert opinions, namely, academic performances (C_1), subject knowledge (C_2), teaching aptitude (C_3), research- experiences (C_4), leadership quality (C_5), personality (C_6), management capacity (C_7) and values (C_8) are considered for recruitment criteria. If four experts are required in the evaluation process, then the five possible alternatives A_i (i= 1, 2, 3, 4, 5) are evaluated by the form of SVNNs under the above eight attributes on the fuzzy concept "excellence". Thus the four single valued neutrosophic decision matrices can be obtained from the four experts and expressed, respectively, as follows:(see Table 1, 2, 3, 4).

Table1: Single valued neutrosophic decision matrix

D_1=

.	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	$\langle .8, .1,.1\rangle$	$\langle .8,.1,.1\rangle$	$\langle .7,.2,.1\rangle$	$\langle .7,.2,.2\rangle$	$\langle .7,.4,.1\rangle$	$\langle .7,.4,.2\rangle$	$\langle .7,.3,.1\rangle$	$\langle .7,.4,.3\rangle$
A_2	$\langle .8,.2,.2\rangle$	$\langle .8,.2,.1\rangle$	$\langle .7,.3,.2\rangle$	$\langle .7,.3,.3\rangle$	$\langle .7,.3,.2\rangle$	$\langle .6,.4,.2\rangle$	$\langle .7,.2,.2\rangle$	$\langle .7,.3,.4\rangle$
A_3	$\langle .8,.1,.2\rangle$	$\langle .8,.3,.2\rangle$	$\langle .7,.4,.3\rangle$	$\langle .7,.3,.1\rangle$	$\langle .7,.2,.3\rangle$	$\langle .6,.3,.3\rangle$	$\langle .7,.1,.3\rangle$	$\langle .7, .3,.3\rangle$
A_4	$\langle .8,.1,.0\rangle$	$\langle .8,.2,.3\rangle$	$\langle .7,.3,.4\rangle$	$\langle .7,.1,.2\rangle$	$\langle .7,.2,.2\rangle$	$\langle .7,.2,.2\rangle$	$\langle .7,.2,.3\rangle$	$\langle .7,.2,.4\rangle$
A_5	$\langle .8,.2,.2\rangle$	$\langle .8,.3,.3\rangle$	$\langle .7,.3,.4\rangle$	$\langle .7,.2,.2\rangle$	$\langle .7,.1,.3\rangle$	$\langle .7,.1,.1\rangle$	$\langle .7,.1,.2\rangle$	$\langle .7,.1,.3\rangle$

Table2: Single valued neutrosophic decision matrix

D_2=

.	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	$\langle .8, .2,.1\rangle$	$\langle .8,.1,.1\rangle$	$\langle .7,.2,.2\rangle$	$\langle .7,.1,.2\rangle$	$\langle .7,.4,.2\rangle$	$\langle .7,.4,.2\rangle$	$\langle .7,.3,.2\rangle$	$\langle .7,.3,.3\rangle$
A_2	$\langle .8,.2,.2\rangle$	$\langle .8,.2,.2\rangle$	$\langle .7,.3,.3\rangle$	$\langle .7,.3,.3\rangle$	$\langle .7,.2,.2\rangle$	$\langle .6,.4,.3\rangle$	$\langle .7,.3,.2\rangle$	$\langle .7,.4,.4\rangle$
A_3	$\langle .8,.2,.2\rangle$	$\langle .8,.3,.3\rangle$	$\langle .7,.3,.3\rangle$	$\langle .7,.3,.2\rangle$	$\langle .7,.3,.3\rangle$	$\langle .6,.3,.3\rangle$	$\langle .7,.2,.3\rangle$	$\langle .7,.2,.3\rangle$
A_4	$\langle .8,.1,.0\rangle$	$\langle .8,.2,.2\rangle$	$\langle .7,.3,.4\rangle$	$\langle .7,.1,.2\rangle$	$\langle .7,.3,.2\rangle$	$\langle .7,.2,.2\rangle$	$\langle .7,.3,.3\rangle$	$\langle .7,.3,.4\rangle$
A_5	$\langle .8,.1,.2\rangle$	$\langle .8,.2,.3\rangle$	$\langle .7,.3,.3\rangle$	$\langle .7,.2,.2\rangle$	$\langle .7,.2,.3\rangle$	$\langle .7,.1,.2\rangle$	$\langle .7,.2,.2\rangle$	$\langle .7,.2,.3\rangle$

Table3: Single valued neutrosophic decision matrix

D_3=

.	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	$\langle .8, .1,.0\rangle$	$\langle .8,.1,.1\rangle$	$\langle .7,.2,.2\rangle$	$\langle .7,.2,.1\rangle$	$\langle .7,.3,.1\rangle$	$\langle .7,.3,.2\rangle$	$\langle .7,.3,.2\rangle$	$\langle .7,.3,.3\rangle$
A_2	$\langle .8,.2,.1\rangle$	$\langle .8,.2,.1\rangle$	$\langle .7,.3,.2\rangle$	$\langle .7,.2,.3\rangle$	$\langle .7,.3,.2\rangle$	$\langle .6,.4,.4\rangle$	$\langle .7,.3,.2\rangle$	$\langle .7,.3,.3\rangle$
A_3	$\langle .8,.2,.2\rangle$	$\langle .8,.2,.2\rangle$	$\langle .7,.3,.3\rangle$	$\langle .7,.3,.2\rangle$	$\langle .7,.2,.2\rangle$	$\langle .6,.2,.3\rangle$	$\langle .7,.2,.3\rangle$	$\langle .7,.3,.4\rangle$
A_4	$\langle .8,.1,.0\rangle$	$\langle .8,.2,.2\rangle$	$\langle .7,.3,.2\rangle$	$\langle .7,.1,.2\rangle$	$\langle .7,.2,.2\rangle$	$\langle .7,.2,.2\rangle$	$\langle .7,.2,.3\rangle$	$\langle .7,.2,.3\rangle$
A_5	$\langle .8,.1,.2\rangle$	$\langle .8,.2,.3\rangle$	$\langle .7,.2,.4\rangle$	$\langle .7,.1,.2\rangle$	$\langle .7,.1,.3\rangle$	$\langle .7,.1,.2\rangle$	$\langle .7,.2,.2\rangle$	$\langle .7,.2,.3\rangle$

Table4: Single valued neutrosophic decision matrix

D_4=

.	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	$\langle .8, .2,.1\rangle$	$\langle .8,.2,.1\rangle$	$\langle .7,.2,.1\rangle$	$\langle .7,.2,.2\rangle$	$\langle .7,.3,.1\rangle$	$\langle .7,.2,.2\rangle$	$\langle .7,.2,.1\rangle$	$\langle .7,.4,.3\rangle$
A_2	$\langle .8,.2,.0\rangle$	$\langle .8,.2,.1\rangle$	$\langle .7,.3,.2\rangle$	$\langle .7,.1,.3\rangle$	$\langle .7,.3,.2\rangle$	$\langle .6,.4,.3\rangle$	$\langle .7,.2,.2\rangle$	$\langle .7,.3,.3\rangle$
A_3	$\langle .8,.1,.2\rangle$	$\langle .8,.2,.2\rangle$	$\langle .7,.3,.3\rangle$	$\langle .7,.3,.2\rangle$	$\langle .7,.2,.2\rangle$	$\langle .6,.3,.2\rangle$	$\langle .7,.3,.3\rangle$	$\langle .7,.3,.3\rangle$
A_4	$\langle .8,.1,.0\rangle$	$\langle .8,.2,.3\rangle$	$\langle .7,.3,.3\rangle$	$\langle .7,.1,.2\rangle$	$\langle .7,.2,.2\rangle$	$\langle .7,.2,.2\rangle$	$\langle .7,.2,.3\rangle$	$\langle .7,.2,.4\rangle$
A_5	$\langle .8,.2,.2\rangle$	$\langle .8,.3,.0\rangle$	$\langle .7,.3,.3\rangle$	$\langle .7,.2,.2\rangle$	$\langle .7,.1,.3\rangle$	$\langle .7,.1,.1\rangle$	$\langle .7,.1,.2\rangle$	$\langle .7,.2,.3\rangle$

Thus, we use the proposed method for single valued neutrosophic group decision-making to get the most suitable teacher. We take α = 0.5 for demonstrating the computing procedure of the proposed method. For the above four decision matrices, the following hybrid score-accuracy matrices are obtained by equation(3):(see Table 5, 6, 7, 8)

Table5: Hybrid score accuracy matrix for D_1

Y_1=

.	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	1.7667	1.7167	1.6000	1.5167	1.5333	1.4500	1.5667	1.3667
A_2	1.6000	1.6833	1.4833	1.4000	1.4833	1.3667	1.5167	1.3167
A_3	1.6333	1.6500	1.3667	1.5667	1.4333	1.3167	1.4667	1.4000
A_4	1.8000	1.5167	1.3167	1.5500	1.5167	1.5167	1.4333	1.3500
A_5	1.6000	1.4833	1.3167	1.5167	1.4667	1.6333	1.5500	1.4667

Table6: Hybrid score accuracy matrix for D_2

Y_2=

.	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	1.6833	1.7167	1.5167	1.5500	1.4500	1.4500	1.4833	1.4000
A_2	1.6000	1.6000	1.4000	1.4000	1.5167	1.2833	1.4833	1.2833
A_3	1.6000	1.4833	1.4000	1.4833	1.4000	1.3167	1.4333	1.4333
A_4	1.8000	1.6000	1.3167	1.5500	1.4833	1.5167	1.4000	1.3167
A_5	1.6333	1.5167	1.4000	1.5167	1.4333	1.5500	1.5167	1.4333

Table7: Hybrid score accuracy matrix for D_3

Y_3=

.	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	1.8000	1.7167	1.5167	1.6000	1.5667	1.4833	1.4833	1.4000
A_2	1.6833	1.6833	1.4833	1.4333	1.4833	1.2000	1.4833	1.4000
A_3	1.6000	1.6000	1.4000	1.4833	1.5167	1.3500	1.4333	1.3167
A_4	1.8000	1.6000	1.4833	1.5500	1.5167	1.5167	1.4333	1.4333
A_5	1.6333	1.5167	1.3500	1.5500	1.4667	1.5500	1.5167	1.4333

Table8: Hybrid score accuracy matrix for D_4

Y_4=

.	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	1.6833	1.6833	1.6000	1.5167	1.5667	1.5167	1.6000	1.3667
A_2	1.7333	1.6833	1.4833	1.4667	1.4833	1.2833	1.5167	1.4000
A_3	1.6333	1.6000	1.4000	1.4833	1.5167	1.4000	1.4000	1.4000
A_4	1.8000	1.5167	1.4000	1.5500	1.5167	1.5167	1.4333	1.3500
A_5	1.6000	1.7333	1.4000	1.5167	1.4667	1.6333	1.5500	1.4333

From the above hybrid score-accuracy matrices, by using equation (4) we can yield the average matrix Y^*.(see Table 9)

Table9: The average matrix

$Y^{*}=$

.	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	1.7208	1.7084	1.5584	1.5459	1.5292	1.4750	1.5333	1.3834
A_2	1.6417	1.6500	1.4625	1.4375	1.4917	1.2833	1.5000	1.3625
A_3	1.6167	1.5833	1.3917	1.5042	1.4792	1.3459	1.4333	1.3875
A_4	1.8000	1.5584	1.3792	1.5500	1.5084	1.5167	1.4250	1.3625
A_5	1.6167	1.5625	1.3667	1.3450	1.4584	1.5917	1.5334	1.4417

From the equations. (5) and (6), we determine the weights of the three decision makers as follows: $\lambda_1 = 0.2505$ $\lambda_2 = 0.2510$ $\lambda_3 = 0.2491$ $\lambda_3 = 0.2494$

Hence, the hybrid score-accuracy values of the different decision makers' evaluations are aggregated[48] by equation (7) and the following collective hybrid score-accuracy matrix can be obtain as follows(see Table 10):

Table10: Collective hybrid score accuracy- matrix

$Y=$

.	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	1.7209	1.7085	1.5584	1.5459	1.5292	1.4751	1.5334	1.3834
A_2	1.6417	1.6500	1.4624	1.4375	1.4918	1.2833	1.5000	1.3624
A_3	1.6168	1.5834	1.3917	1.5043	1.4792	1.3458	1.4332	1.3875
A_4	1.8001	1.5584	1.3793	1.5500	1.5085	1.5167	1.4250	1.3626
A_5	1.6167	1.5626	1.3667	1.3451	1.4584	1.5918	1.5334	1.4417

Assume that the information about attribute weights is incompletely known weight vectors, $0.1 \le w_1 \le 0.2$, $0.1 \le w_2 \le 0.2$, $0.1 \le w_3 \le 0.2$, $0.1 \le w_4 \le 0.2$, $0.1 \le w_5 \le 0.2$, $0.1 \le w_6 \le 0.2$, $0.1 \le w_7 \le 0.2$, $0.1 \le w_8 \le 0.2$ given by the decision makers,

By using the linear programming model (8), we obtain the weight vector of the attributes as:

$W = [0.2, 0.2, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1]^{T}$

By applying eqation (9), we can calculate the overall hybrid score-accuracy values $M(A_i)$ (i=1, 2, 3, 4, 5):

$M(A_1) = 1.58842$, $M(A_2) = 1.51208$, $M(A_3) = 1.49421$, $M(A_4) = 1.54591$, $M(A_5) = 1.50957$

According to the above values of $M(A_i)$ (i= 1, 2, 3, 4, 5), the ranking order of the alternatives is

$A_1 > A_4 > A_2 > A_5 > A_3$. Then, the alternative A_1 is the best teacher.

By similar computing procedures, for different values of α the ranking orders of the teachers are shown in the Table 11.

Section VI

Conclusion

In this paper we employ the score and accuracy functions, hybrid score-accuracy functions of SVNNs to recruitt best teacher for higher education under 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 these weight models mainly decrease the effect of some unreasonable evaluations, e.g. the decision makers may have personal biases and some individuals may give unduly high or unduly low preference values with respect to their preferred or repugnant objects. Then, we use overall evaluation formulae of the weighted hybrid score-accuracy functions for each alternative to rank the alternatives and select the most desirable teacher. The advantages of the model for group decision-making methods with single valued neutrosophic information is provide simple calculations and good flexibility but also 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 continue working in the extension and application of the methods to other domains, such as best raw material selection for industries.

Table11: The ranking order of the teachers taking different values of α

α	$M(A_i)$	Ranking order
0.0	$M(A_1)$=1.61872, $M(A_2)$=1.54988, $M(A_3)$=1.54441, $M(A_4)$=1.56961, $M(A_5)$=1.54697	$A_1 > A_4 > A_2 > A_5 > A_3$.
0.3	$M(A_1)$=1.60052, $M(A_2)$=1.52518, $M(A_3)$=1.51429, $M(A_4)$=1.55541, $M(A_5)$=1.52317	$A_1 > A_4 > A_2 > A_5 > A_3$.
0.5	$M(A_1)$=1.58842, $M(A_2)$=1.51208, $M(A_3)$=1.49426, $M(A_4)$=1.54591, $M(A_5)$=1.50957	$A_1 > A_4 > A_2 > A_5 > A_3$.
0.7	$M(A_1)$=1.57632, $M(A_2)$=1.49898, $M(A_3)$=1.47404, $M(A_4)$=1.53651, $M(A_5)$=1.49307	$A_1 > A_4 > A_2 > A_5 > A_3$.
1.0	$M(A_1)$=1.55822, $M(A_2)$=1.48928, $M(A_3)$=1.44392, $M(A_4)$=1.52231, $M(A_5)$=1.48467	$A_1 > A_4 > A_2 > A_5 > A_3$.

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