A Neutrosophic Evaluation Method of Engineering Certification Teaching Effect Based on Improved Entropy Optimization Model and Its Application in Student Clustering

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Abstract: To realize the all-around assessment of teaching quality in the context of engineering education accreditation, this study proposes a single-valued neutrosophic information entropy and a novel assessment method of teaching effectiveness. In this proposed assessment model, an optimization model is structured based on the minimum information entropy value of single-valued neutrosophic sets (SvNSs). In this study, the primary innovation is that by using the structured model, the attribute weights are extracted from the given deterministic information. The main work of this study is summarized as follows. Firstly, aiming at the engineering certification problem, this study proposes an improved single-value neutrosophic information entropy formula to enhance the effectiveness of the engineering certification results. Secondly, this paper establishes an optimization model based on the minimum information entropy value and provides a method for assigning weight values. Thirdly, this study proposes an improved evaluation method for teaching effect, which provides a novel idea for engineering certification. Thereafter, a case study is presented to demonstrate the effectiveness and practicality of the proposed model.

Keywords: single-valued neutrosophic set; single-valued neutrosophic information entropy; engineering education certification; student clustering

1. Introduction

Engineering accreditation serves as a globally recognized system for ensuring the quality of engineering education, and is essential for achieving international recognition of both engineering education and qualifications. The central aspect of engineering certification is to ensure that engineering graduates meet industry-recognized standards [1]. In 2016, China formally joined the Washington Agreement, introduced advanced results-oriented education concepts, and promoted the certification of undergraduate engineering education [2]. However, the current evaluation of teaching quality is mainly the evaluation of course achievement degrees, which predominantly test the student's mastery of the course content. The evaluation method is single and subjective, and the evaluation of graduation requirement achievement is not comprehensive. In addition, assessment methods to be met for graduation requirements have some problems, such as difficulty in quantifying graduation requirements and unscientific assessment methods. Therefore, aiming at the fuzzy and uncertain information in the teaching evaluation process, this paper gives an improved information entropy function based on the theory of neutrosophic sets. Three evaluation indexes are used to comprehensively assess the teaching effectiveness, which provides a novel method for university engineering accreditation.

The accreditation of engineering education programs began in the 1930s as a form of professional certification, and has become the most influential certification system in the world. To evaluate whether students have met the graduation requirements, scholars typically use the 12 graduation requirements outlined in the Washington Accord as a benchmark. Khan et al. [3] took the civil engineering major of King Saudi University as an example. They mapped the students' learning achievements one by one and established a mapping table of learning achievements and curriculum achievements. Jiao et al. [4] established 12 graduation requirements according to the training objectives of surveying and mapping engineering professionals in their colleges and universities and decomposed each graduation requirement into lots of evaluation indicators. One approach used in their study was to calculate the achievement degree of graduation requirements as the minimum value among all the evaluation values of the indicators. Qu and Fan [5] constructed an evaluation index system based on the network analytic hierarchy process from four aspects: teaching links, teacher quality, teaching resources, and teaching preparation.

Smarandache proposed the concept of neutrosophic sets in 1998 [6]. Neutrosophic sets consist of truth-membership degrees, indeterminacy-membership degrees, and falsity-membership degrees, which can more clearly express uncertain and inconsistent information. After that, neutrosophic sets have received the extensive attention and research of scholars. Ye [7] developed the notion of simplified neutrosophic sets, and provided their set relationships and rules for operations. Then, single-valued neutrosophic sets (SvNSs) are also widely used in group decision-making problems involving multiple attributes. Ye et al. [8] put forward the distance formula of SvNSs and gave a novel approach for multi-attribute decision-making based on SvNSs. Aydogdu [9] gave the measurement formula of entropy and similarity. Many scholars also combined the neutrosophic set with a variety of traditional multiple criteria decision-making methods. Peng et al. [10] introduced new operations for simplified neutrosophic numbers and devised a comparison approach based on the existing research on intuitionistic fuzzy numbers, and then applied them to the medical field. Peng et al. [11] proposed a novel approach to tackle multi-criteria group decision-making problems where weight information is unknown, and evaluation values are expressed as probability multi-valued neutrosophic numbers. They successfully applied this method to solve the vendor selection problem. Ye [12] introduced a novel method for measuring the vector similarity between simplified neutrosophic sets and implemented it in the domain of investment and risk management.

In dealing with process on uncertain information, information measurement is a very important content, which has attracted the extensive attention of scholars. Tan et al. [13] introduced the notion of hesitant fuzzy index entropy, which enabled the construction of a multi-attribute decision-making model based on an entropy weight method. Wei et al. [14] introduced a new model for hesitant fuzzy entropy that is based on the mean and variance of hesitation fuzzy elements. Hu et al. [15] proposed an alternative hesitation fuzzy entropy model that is derived from the perspective of hesitation fuzzy similarity. Xu et al. [16] proposed several measurement formulae for fuzzy entropy and cross entropy of hesitation fuzzy sets. Liang et al. [17] constructed a model for multi-attribute decision-making that utilized the scoring function and minimum relative entropy principle. In the field of fuzzy decision-making, Vlachos and Sergiadis [18] presented a discrimination information method for intuitionistic fuzzy sets and introduced the concept of cross entropy. Liu et al. [19] proposed three novel formulae for probability hesitation fuzzy entropy and provided axiomatic definitions for these measures. They applied these measures to solve multi-attribute decision-making problems.

To introduce the work efficiently, the following sections of this study are organized as follows. Section 2 provides a review of concepts related to SvNSs and introduces an improved single-valued neutrosophic information entropy function. Section 3 presents an evaluation model based on single-valued neutrosophic information entropy and explains how the evaluation mechanism is optimized. Section 4 verifies the feasibility of the presented model through an example. Section 5 summarizes the full text. The specific research framework is shown in Figure 1.

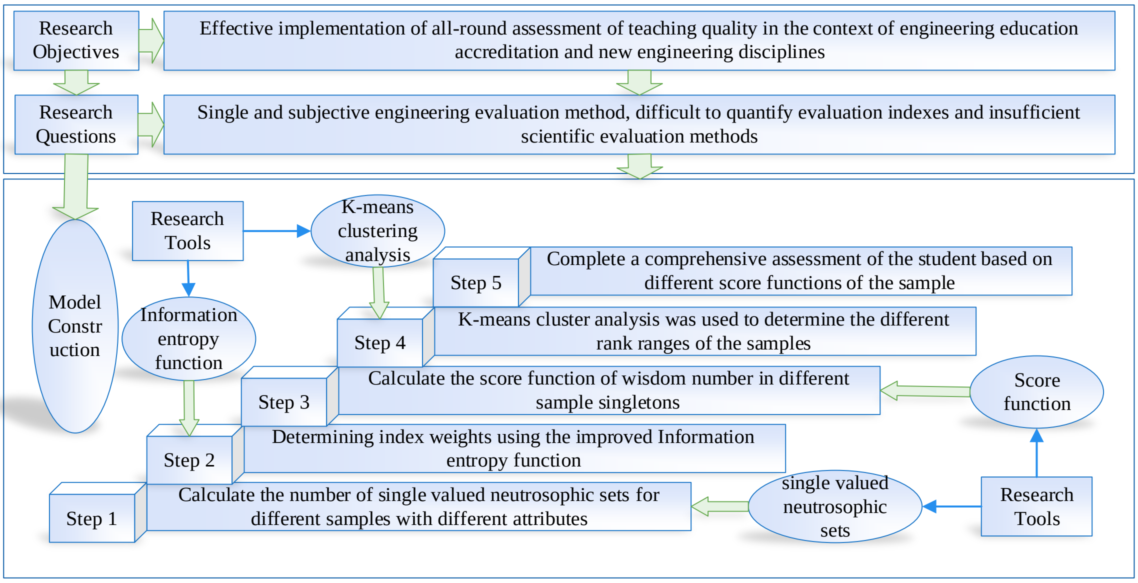

Figure 1. Research framework

2. Preliminary Knowledge

In this section, the preliminary concepts on SvNSs and single-valued neutrosophic information entropy are introduced.

2.1. Concepts on SvNSs

Definition 1. If X is a universe set and x is any one element in X, then the SvNS A in X is expressed as $A = \{< x, \alpha_1(x),\ \alpha_2(x),\ \alpha_3(x) > | x \in X\}$ [20], where $\alpha_1(x),\ \alpha_2(x),\ \alpha_3(x) \in [0,\ 1]$ are the truth-membership degree, the indeterminacy-membership degree, and the falsity-membership degree, respectively. Then, the element $< x, \alpha_1(x),\ \alpha_2(x),\ \alpha_3(x) >$ in A is simply denoted as the single-valued neutrosophic number (SvNN) $a =< \alpha_1, \alpha_2, \alpha_3 >$.

Definition 2. If $a_1 =< \alpha_1^1, \alpha_2^1, \alpha_3^1 >$ and $a_2 =< \alpha_1^2, \alpha_2^2, \alpha_3^2 >$ are two SvNNs, then there are the following algorithms [21]:

(1) $a_1 \cup a_2 = \left\langle \max\left(\alpha_1^1, \alpha_1^2\right), \min\left(\alpha_2^1, \alpha_2^2\right), \min\left(\alpha_3^1, \alpha_3^2\right) \right\rangle$;

(2) $a_1 \cap a_2 = \left\langle \min\left(\alpha_1^1, \alpha_1^2\right), \max\left(\alpha_2^1, \alpha_2^2\right), \max\left(\alpha_3^1, \alpha_3^2\right) \right\rangle$;

(3) $a_1 \oplus a_2 = \left\langle \alpha_1^1 + \alpha_1^2 - \alpha_1^1, \alpha_1^2, \alpha_2^1\alpha_2^2, \alpha_3^1\alpha_3^2 \right\rangle$;

(4) $a_1 \otimes a_2 = \left\langle \alpha_1^1\alpha_1^2, \alpha_2^1 + \alpha_2^2 - \alpha_2^1, \alpha_2^2, \alpha_3^1 + \alpha_3^2 - \alpha_3^1\alpha_3^2 \right\rangle$;

(5) $\lambda a_1 = \left\langle 1 - \left(1 - \alpha_1^1\right)^{\lambda}, (\alpha_2^1)^{\lambda}, (\alpha_3^1)^{\lambda} \right\rangle, \lambda > 0$;

(6) $a_1^{\lambda}=\left\langle (\alpha_1^1)^{\lambda}, 1-\left(1-\alpha_2^1\right)^{\lambda}, 1-\left(1-\alpha_3^1\right)^{\lambda}\right\rangle, \lambda>0$;

(7) The complement of a_1 is $a_1^c=\left\langle \alpha_3^1, 1-\alpha_2^1, \alpha_1^1\right\rangle$.

2.2 Single-Valued Neutrosophic Information Entropy

Definition 3. Inspired by the classical hesitant fuzzy entropy function [22] , this study proposes the information entropy function of the SvNN. Let $a=<\alpha_1,\alpha_2,\alpha_3>$ be SvNN. According to the trigonometric functions, the information entropy function of the SvNN a is represented as

$$E_1(a)=\frac{1}{3}\sum_{t=1}^{3}\frac{\left(\sqrt{2}\sin\frac{\left|\alpha_t-(\alpha_t)^c\right|+1}{4}\pi+\sqrt{2}\cos\frac{\left|\alpha_t-(\alpha_t)^c\right|+1}{4}\pi-\sqrt{2}\right)}{2-\sqrt{2}} \quad . \quad (1)$$

Definition 4. Let $a=<\alpha_1,\alpha_2,\alpha_3>$ be SvNN, then the single-valued neutrosophic information entropy function $E_1(a)$ satisfies the following properties:

(E1) When $\alpha_t\in[0,0.5]$ for $t=1,2,3,$ the function $E_1(a)$ is a monotonic increasing function. When $\alpha_t\in[0.5,1]$ for $t=1,2,3,$ the function $E_1(a)$ is a monotonic decreasing function.

(E2) When $a=<\alpha_1,\alpha_2,\alpha_3> \;=\; <0.5,0.5,0.5>$, the function $E_1(a)$ has the maximum value.

(E3) $E_1(a)=0$ iff a is a crisp set.

(E4) $E_1(a)=E_1(a^c)$.

Proof:

First, the following functions are constructed:

$$f(x)=\left(\sqrt{2}\sin\frac{x}{4}\pi+\sqrt{2}\cos\frac{x}{4}\pi-\sqrt{2}\right), x\in[1,2]. \quad (2)$$

Then

$$f'(x)=\frac{df(x)}{dx}=\frac{\pi}{2\sqrt{2}}\left(\cos\frac{x}{4}\pi-\sin\frac{x}{4}\pi\right), x\in[1,2]. \quad (3)$$

$$f''(x)=\frac{d^2f(x)}{dx^2}=\frac{-\pi^2}{8\sqrt{2}}\left(\sin\frac{x}{4}\pi+\cos\frac{x}{4}\pi\right), x\in[1,2]. \quad (4)$$

Here $x=|a_t-(a_t)^c|+1$ for $t=1, 2, 3$. When $x\in[1,2]$, $f'(x)$ is always less than or equal to 0, then $f(x)$ is a monotone decreasing function. Therefore, if $x=1$, $|a_t-(a_t)^c|=0,$ and $a_t=0.5$, $f(x)$ takes the maximum value $f_{max}(x)=2-\sqrt{2}$ and $E_1(a)=1$. If and only if $x=2$ and $|a_t-(a_t)^c|=1$, it is clear that $a_t=0$ or 1. Then $f(x)$ takes the minimum value $f_{min}(x)=0$, i.e, $E_1(a)=0$. When the $\alpha_t\in[0,0.5]$ for $t=1,2,3,$ the function $E_1(a)$ is a monotonic increasing function. When the $\alpha_t\in[0.5,1]$ for $t=1,2,3,$ the function $E(a)$ is a monotonic decreasing function. Therefore, (E1) is obtained.

When $x=1$ and $a=a^c=<0.5,0.5,0.5>$, there is $|a_t-(a_t)^c|=0$ $(t=1,2,3)$. Then, the information entropy $E_1(a)$ has the maximum value. Therefore, (E2) is obtained.

When a is a crisp set, i.e., $|a_t-(a_t)^c|=0$ $(t=1,2,3)$ and $x=2$. It implies that either $a=<1, 0, 0>$ and $a^c=<0,1,1>$ or $a=<0,0,1>$ and $a^c=<1,1,0>$, then the information entropy value $E_1(a)=0$. Obviously, it also gets $|a_t-(a_t)^c|=|(a_t)^c-a_t|$ and $E_1(a)=E_1(a^c)$. Therefore, (E3) and (E4) are obtained.

3. Model Construction

To improve the evaluation mechanism of colleges and universities, this study proposes three evaluation indicators to achieve a comprehensive evaluation of students. In the process of evaluation, the graduation requirements of different majors are divided into several indicators, and curriculum objectives are set for the indicators of graduation requirements. Each curriculum objective corresponds to different graduation indicators. Teachers set exam questions for different graduation indicators and course objectives. For the sake of clarity, we use an evaluation sample as an illustration of the above correspondence. The corresponding relationship of the sample evaluation bases is shown in Table 1.

In this study, the comprehensive evaluation of college students is regarded as a multi-attribute evaluation problem, and all the students in the class are regarded as the evaluation set $X = \{x_1, x_2, \cdots, x_m\}$. Then, $C = \{c_1, c_2, \cdots, c_n\}$ is denoted as an attribute indicator set. Through the three main attribute indicators, we evaluate the comprehensive quality of students, including the overall fulfillment level of the graduation requirements c_1, the achievement degree of curriculum objectives c_2 and the overall achievement degree c_3. Therefore, the attribute indicator set is denoted as $C = \{c_1, c_2, c_3\}$, and then the weight vector of the attribute indicator set is specified as $\omega_j = \{\omega_1, \omega_2, \omega_3\}$, where $0 \le \omega_j \le 1$, and $\sum_{j=1}^{3} \omega_j = 1$. The school evaluates each student according to the SvNN, the SvNNs of different students form the SvNN decision matrix $D = (a_{ij})_{m\times n}$. Since the attribute indicators in this evaluation problem are all benefit-based attributes and have no cost-based attributes, it is unnecessary to normalize the matrix D. The evaluation process of the teaching effect is as follows.

Step 1: Calculate the SvNN of different samples. $O_i (i = 1, 2, \dots, k)$ is denoted as the original score, G_i is denoted as the achievement degree of each assessment basis, and G_i is named the total achievement degree of the curriculum graduation requirement index. R_i is denoted as the assessment result, W_i is denoted as the index weight of the corresponding graduation requirements, A_i is named the average score of each major question, and l is denoted as the index point of the graduation requirements. M_i is denoted as the sub-item weight of the curriculum objectives. Thus, $R_i = W_i \cdot A_j$. Then, the truth-membership degrees of c_1 and c_2 are defined as

$$\alpha_1^{c_1} = \frac{1}{n} \sum_{i=1}^{k} \frac{R_i}{O_i}, \quad \sum_{i=1}^{k} O_i = 100, \tag{5}$$

$$\alpha_1^{c_2} = \frac{1}{l} \sum_{j=1}^{l} \sum_{i=j}^{j+1} \frac{O_i G_i}{O_i + O_{i+1}}. \tag{6}$$

The assessment results of this study are divided into final exam scores and usual performance. The weight of the final exam scores is 70%, while the weight of the usual performance is 30%. The average score of the usual performance is recorded as A_i. Then, the truth-membership degree of c_3 is recorded as

$$\alpha_1^{c_3} = \frac{1}{100} \left(\sum_{i=1}^{k} R_i \cdot 0.7 + \sum_{i=1}^{k} A_{si} \cdot 0.3 \right). \tag{7}$$

The falsity-membership degrees of c_1, c_2 and c_3 are defined as

$$\alpha_3^{c_1} = 1 - \frac{1}{k} \sum_{i=1}^{k} \frac{W_i}{G_i}, \tag{8}$$

$$\alpha_3^{c_2} = 1 - \frac{1}{100} \sum_{i=1}^{k} R_i \cdot M_i, \tag{9}$$

$$\alpha_3^{c_3} = 1 - \frac{1}{100}\left(\sum_{i=1}^{k} R_i - \sum_{i=1}^{k} R_i W_i\right). \tag{10}$$

The indeterminacy-membership degrees of c_1, c_2 and c_3 are defined as

$$\alpha_2^{c_1} = \cos\left[\frac{\pi}{2}\cos\left(\frac{\pi(\alpha_1^{c_1} - \alpha_3^{c_1})}{2}\right)\right], \tag{11}$$

$$\alpha_2^{c_2} = \cos\left[\frac{\pi}{2}\cos\left(\frac{\pi(\alpha_1^{c_2} - \alpha_3^{c_2})}{2}\right)\right], \tag{12}$$

$$\alpha_2^{c_3} = \cos\left[\frac{\pi}{2}\cos\left(\frac{\pi(\alpha_1^{c_3} - \alpha_3^{c_3})}{2}\right)\right]. \tag{13}$$

Therefore, the corresponding SvNNs of different students are obtained.

Table 1. Corresponding relationship of sample evaluation bases

Course objective	**Indicator of graduation requirements**		**Assessment basis**			
	Index point of graduation requirements	**Weight**	**Basis**	**Score**	**Examination result : Usual result**	**Achievement degree of the assessment basis**
Course objective 1	1-4	100%	First question	10	40% : 60%	0.71
	8-3	40%	Third question	28		0.86
Course objective 2	4-3	50%	Second question	10		0.5
	5-1	40%	Third question	28		0.86
Course objective 3	4-1	50%	Second question	10		0.5
	11-1	20%	Third question	14		0.86

Step 2: Determine the index weight. To enhance the rationality of the evaluation process, each index weight is determined by calculating neutrosophic entropy. To maximize the reliance of the evaluation process on the available information, the objective function is established by determining the indicator weight. It uses the minimum entropy value of neutrosophic information to ensure that the evaluation process relies on the most determinate information possibility. The number of evaluation objects is m. The information entropy function $E(c_j), j = \{1, 2, 3\}$ of each attribute is defined as

$$E(c_j) = \frac{1}{m}\sum_{i=1}^{m} E_1(a_{ij}),\ j = 1, 2, 3, \tag{14}$$

where a_{ij} is defined as the SvNN of the j-th indicator on the i-th assessment object and $E_1(a_{ij})$ is the information entropy function of the SvNN a_{ij}.

To reduce the influence of uncertain information on the evaluation outcomes, we establish an optimization model with the goal function J of minimizing the entropy value. According to Eq. (1), the optimization model is defined as

$$\min J = \sum_{j=1}^{3} E(c_j)\omega_j$$
$$s.t. \begin{cases} \sum_{j=1}^{3} \omega_j = 1, \omega_j \geq 0. \\ 0 \leq E(c_j) \leq 1 \end{cases} \tag{15}$$

The optimization model is solved by the Lagrange multiplier method, and then the weight of each attribute is obtained finally.

Step 3: Calculate the score function of the SvNN [23]. The score function of the SvNN $a_{ij} = < \alpha_1^{ij}, \alpha_2^{ij}, \alpha_3^{ij} >$ is denoted as $S(a_{ij})$ for $S(a_{ij}) \in [0,100]$ and defined as follows:

$$S(a_{ij}) = 50\sqrt{2} \cdot \mathrm{sgn}(\alpha_1^{ij} - \alpha_2^{ij} + \left(\frac{\alpha_1^{ij} - \alpha_2^{ij}}{\alpha_1^{ij} + \alpha_2^{ij}}\right)\alpha_3^{ij})\sqrt{\left|\alpha_1^{ij} - \alpha_2^{ij} + \left(\frac{\alpha_1^{ij} - \alpha_2^{ij}}{\alpha_1^{ij} + \alpha_2^{ij}}\right)\alpha_3^{ij}\right|}. \tag{16}$$

For convenience, set $\alpha_1^{ij} - \alpha_2^{ij} + (\alpha_1^{ij} - \alpha_2^{ij})\alpha_3^{ij}/(\alpha_1^{ij} + \alpha_2^{ij}) = x$. Then, the score function is defined as

$$S(\alpha_{ij}) = 50\sqrt{2} \cdot \mathrm{sgn}(x)\sqrt{|x|},$$

where $\mathrm{sgn}(x)$ is a symbolic function, which is defined as

$$\mathrm{sgn}(x) = \begin{cases} 1, & x \neq 0 \\ 0, & x = 0 \end{cases}.$$

According to Eq. (16), the comprehensive ability evaluation matrix R of students is indicated by

$$R = \begin{bmatrix} S(a_{11}) & S(a_{12}) & S(a_{13}) & \dots & S(a_{1m}) \\ S(a_{21}) & S(a_{22}) & S(a_{23}) & \dots & S(a_{2m}) \\ S(a_{31}) & S(a_{32}) & S(a_{33}) & \dots & S(a_{3m}) \end{bmatrix}^T.$$

Then, the evaluation result vector D is defined as

$$D = R \cdot \omega_j = (d_1, d_2, d_3, \cdots, d_m). \tag{17}$$

Step 4: Determine the value range of the evaluation grade. To determine the levels of different evaluation indicators, this study employs clustering analysis to sample data. In this situation, students are divided into five grades according to different indicators. The evaluation grades are set as $V = \{v_1, v_2, v_3, v_4, v_5\}$. The five grades correspond to five evaluations: excellent, good, fair, poor, and very poor. Then, the K-means clustering analysis method [24] is adopted in this study, and the specific calculation method is given as follows.

First, five sample data are randomly selected as the initial cluster center $k_i (i = 1, 2, 3, 4, 5)$ in the evaluation matrix. Each element in the evaluation matrix is recorded as t_m. The distance d_i from the element t_m in row m to the cluster center k_i is marked as

$$d_i(t_m, k_i) = \sqrt{(t_{1m} - k_{i1})^2 + (t_{2m} - k_{i2})^2 + (t_{3m} - s_{i3})^2}. \tag{18}$$

Once the distance between each sample and each cluster center is calculated, allocate each sample to the nearest cluster center category. After all samples are allocated, recalculate the positions of the five cluster centers. The calculation formula of cluster centers is defined as

$$k_i = \frac{1}{N}\sum_{i=1}^{N} d_i \,, \tag{19}$$

where k_i is named the new cluster center, d_i is named the the distance from the sample in the cluster center to the cluster center, and the number of samples belonging to the cluster center is denoted as N. Once the new cluster center is obtained, the distance between each sample and the new cluster center is calculated again. The process of recalculating the new cluster center and the distance is repeated until the cluster centers no longer change significantly or reach a predetermined convergence criterion. The final position of the cluster center is the critical point of the evaluation grade.

Step 5: The Euclidean distance between each sample point and the five cluster centers is calculated by using Equation (16). The cluster center with the smallest distance from the sample point is the cluster of the category to which the sample belongs. Based on the aforementioned five steps, the neutrosophic assessment of engineering certification teaching effect is realized.

4. Case Analysis

This section presents an example to demonstrate the model described above. We select 10 students as the evaluation set $X = \{x_1, x_2, \cdots \ , x_{10}\}$. Three evaluation indicators are selected as the attribute indicator set $C = \{c_1, c_2, c_3\}$. Score registration form is shown in Table 2. The evaluation process is addressed as follows.

Step 1: Calculate SvNNs of different samples. According to Eqs. (5)-(7), we obtain the truth-membership values of $\alpha_1^{c_1}$, $\alpha_1^{c_2}$, and $\alpha_1^{c_3}$. According to Eqs. (8)-(10), we get the falsity-membership values of $\alpha_3^{c_1}$, $\alpha_3^{c_2}$, and $\alpha_3^{c_3}$. According to Eqs. (11)-(13), we obtain that the indeterminacy-membership value of $\alpha_2^{c_1}$, $\alpha_2^{c_2}$, and $\alpha_2^{c_3}$. The course achievement rating scale is shown in Table 3. Then, the neutrosophic set matrix A of 10 samples is

$$A = \begin{bmatrix} <0.773, 0.057, 0.601> & <0.778, 0.164, 0.483> & <0.847, 0.081, 0.642> \\ <0.776, 0.063, 0.596> & <0.775, 0.160, 0.485> & <0.857, 0.089, 0.642> \\ <0.807, 0.096, 0.583> & <0.808, 0.172, 0.507> & <0.887, 0.129, 0.627> \\ <0.816, 0.107, 0.580> & <0.819, 0.177, 0.513> & <0.900, 0.152, 0.623> \\ <0.867, 0.186, 0.553> & <0.875, 0.209, 0.541> & <0.947, 0.229, 0.597> \\ <0.879, 0.207, 0.547> & <0.882, 0.212, 0.546> & <0.959, 0.250, 0.593> \\ <0.880, 0.204, 0.550> & <0.884, 0.217, 0.544> & <0.961, 0.254, 0.030> \\ <0.883, 0.210, 0.546> & <0.884, 0.212, 0.548> & <0.973, 0.270, 0.592> \\ <0.890, 0.223, 0.545> & <0.893, 0.220, 0.551> & <0.992, 0.301, 0.588> \\ <0.880, 0.217, 0.540> & <0.882, 0.212, 0.546> & <0.990, 0.291, 0.593> \end{bmatrix}.$$

Step 2: The information entropy functions are calculated according to Eqs. (1) and (14). We get $E(c_1) = 0.688$, $E(c_2) = 0.701$, and $E(c_3) = 0.572$. When the calculation results are substituted into the Eq. (15), the index weight results are obtained as follows:

$$\omega = \left(0.2764, 0.2593, 0.4643\right)^T.$$

Step 3: According to Eq. (16), we obtain that the score function values of SvNNs, and then the evaluation matrix R is obtained as follows:

$$R = \begin{bmatrix} 78.56 & 78.09 & 76.49 & 75.98 & 72.06 & 71.08 & 71.38 & 70.78 & 70.48 & 70.33 \\ 68.15 & 68.34 & 69.46 & 69.74 & 70.65 & 70.87 & 70.59 & 70.99 & 70.92 & 70.85 \\ 80.50 & 80.29 & 78.29 & 77.17 & 73.57 & 72.69 & 72.51 & 72.03 & 70.89 & 73.57 \end{bmatrix}^T.$$

According to Eq. (17), the evaluation result vector D is obtained as follows:

$$D = R \cdot \omega = \left(75.76, 76.58, 75.50, 74.91, 72.40, 71.77, 71.69, 71.41, 71.97\right)^T .$$

Step 4: Determine the value range of the evaluation grade. Students are divided into five grades according to different indicator values. The set of evaluation grades is represented as $V = \{v_1, v_2, v_3, v_4, v_5\}$. The five grades $v_1, v_2, \ldots, v_5$ correspond to five evaluations: excellent, good, general, poor, and very poor. In order to better present the clustering effect, 300 SvNNs are selected for clustering analysis. The clustering results are shown in Figures 2, 3, 4. By iterating through Eq. (18) and Eq. (19), sample clustering is achieved. The clustering result of SvNFNs is shown in Table 4, and then the final evaluation results are shown in Figure 5.

Step 5: Eq. (16) is used to calculate the score of cluster center points, and then the results are given as follows:

$$S_{v_1} = 67.91, S_{v_2} = 69.28, S_{v_3} = 69.51, S_{v_4} = 72.3, \text{ and } S_{v_5} = 72.69.$$

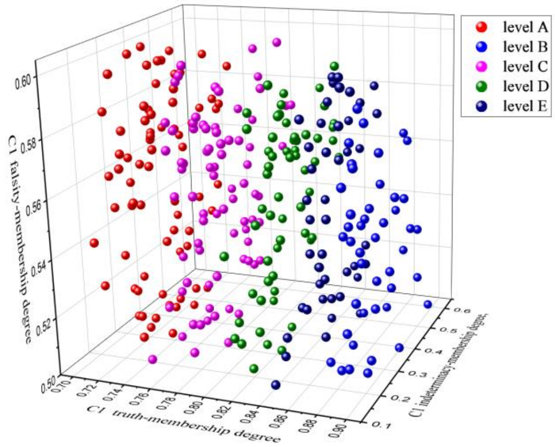

Figure 2. Clustering results of the attribute c_1

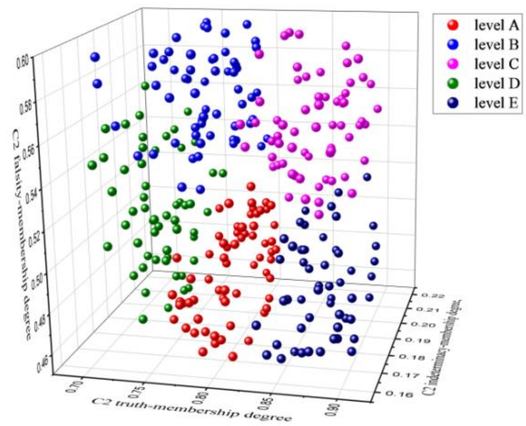

Figure 3. Clustering results of the attribute c_2

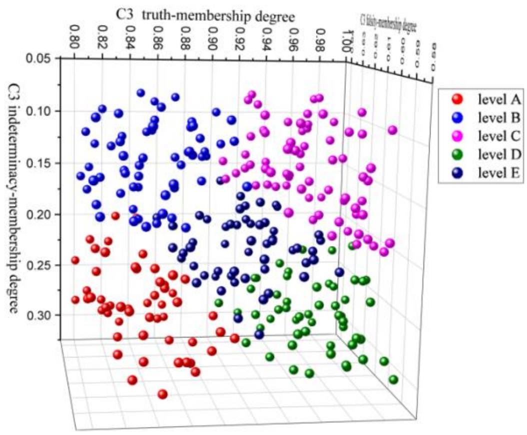

Figure 4. Clustering results of the attribute c_3

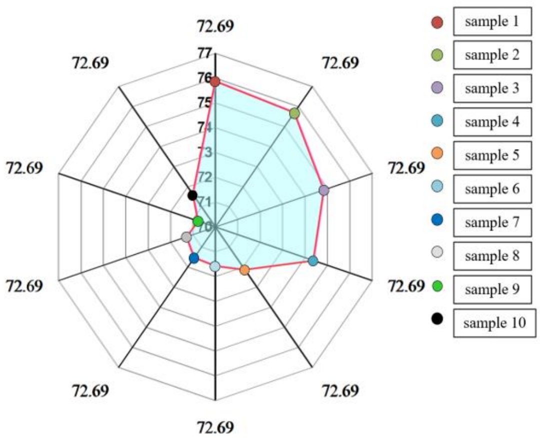

Figure 5. Comparison of the sample results

We calculate the distance between the score function of each sample point and the score function of each cluster center point based on Eq. (18). The shortest distance value is used as the category determination criterion so as to achieve clustering and evaluation of different samples. The maximum score function value of randomly selected sample points is 72.69. The larger the sample point value, the closer to the maximum value. The evaluation results indicate that the samples 1, 2, 3, 4 belong to the grade v_1, the samples 5, 6, 7, 8, 10 belong to the grade v_2, and the sample 9 belongs to the grade v_3. Finally, the comprehensive evaluation of students is completed.

Table 2. Score registration form

Sample		1	2	3	4	5	6	7	8	9	10
Course	Question1	5.672	5.698	6.703	6.749	6.823	6.697	7.031	7.092	5.642	5.643
objective 1	Question2	5.667	5.693	6.078	6.234	6.476	6.897	6.903	7.112	6.345	6.345
Course	Question 3	5.612	5.758	5.972	6.284	6.172	6.223	6.012	5.685	5.712	5.63
objective 2	Question 4	6.742	6.983	6.982	6.832	7.932	7.842	7.844	7.761	7.851	7.851
Course	Question 3	5.923	5.783	6.234	6.756	6.823	6.881	7.516	7.722	7.541	7.341
objective 3	Question 1	9.629	9.742	9.923	9.472	9.827	10.639	11.923	10.963	11.685	11.477
Course	Question 2	8.645	8.923	8.912	9.042	9.142	9.972	9.662	10.294	10.354	10.354
objective 4	Question 5	5.424	4.623	4.816	4.923	5.823	5.743	5.623	5.256	5.864	5.625
Course	Question 4	12.735	13.803	12.995	13.823	14.886	12.953	13.843	14.263	14.852	14.867
objective 5	Question 5	11.983	11.472	12.727	12.043	13.862	14.512	11.482	12.345	14.872	14.532
Peacetime performance		97.832	97.992	98.872	98.982	99.123	99.623	99.113	99.276	97.872	97.525

Table 3. Course achievement rating scale

Basis	Score (percentage system)	Score (original)	Assessment result (original score)	Achievement degree of each assessment basis	Sub-item weight of course objectives	Achievement of course objectives by item	Sub-item weight of index points required by course graduation
Question 1	5.6	8	6.375	0.8	50%	0.797	33%
Question 2	5.6	8	6.375	0.8	50%		33%
Question 3	5.6	8	5.906	0.74	50%	0.836	33%
Question 4	5.6	8	7.462	0.93	50%		50%
Question 3	5.6	8	6.852	0.86	40%	0.869	50%
Question 1	8.4	12	10.528	0.88	60%		40%
Question 2	8.4	12	9.53	0.79	66.70%	0.828	40%
Question 5	4.2	6	5.372	0.9	33.30%		20%
Question 4	10.5	15	13.902	0.93	50%	0.896	50%
Question 5	10.5	15	12.983	0.87	50%		50%

Table 4. Student clustering results

Attribute	Iteration	Membership degree	Level A	Level B	Level C	Level D	Level E
		Truth-membership degree	0.734	0.799	0.852	0.755	0.868
c_1	10	Indeterminacy-membership degree	0.193	0.188	0.196	0.189	0.189
		Falsity-membership degree	0.495	0.486	0.557	0.567	0.479
		Truth-membership degree	0.791	0.768	0.855	0.725	0.866
c_2	15	Indeterminacy-membership degree	0.188	0.19	0.197	0.191	0.189
		Falsity-membership degree	0.483	0.57	0.553	0.51	0.478
		Truth-membership degree	0.843	0.941	0.937	0.95	0.846
c_3	10	Indeterminacy-membership degree	0.134	0.113	0.186	0.266	0.248
		Falsity-membership degree	0.612	0.614	0.61	0.611	0.61

5. Conclusions

According to the introduced case, the primary contributions of this study are as follows.

Firstly, three indicators of students' performance were obtained as the achievement of graduation requirements, the achievement of course objectives, and the achievement of grades. By using the three indicators, a kind of comprehensive assessment method for teaching effectiveness was proposed in SvNN setting.

Secondly, we proposed an improved single-valued neutrosophic information entropy function and an optimization model for determining the weights of the three indicators. However, the weights of the three indicators depend entirely on the objective information given, without any subjective information.

Thirdly, we proposed an improved evaluation method for teaching effect, which realized the comprehensive evaluation and cluster of students. This approach offered a novel idea for engineering certification.

The proposed effect of this study is that students can adjust their learning programs according to their achievement of graduation requirements and promote their overall development. Based on the achievement of the indicators, teaching managers can assess the rationality of the training program and the pedagogical effectiveness of the course so as to further improve the student training system. At present, there are some limitations to this study. The selection of the initial cluster center can affect the clustering results during the clustering process. Therefore, in future research, the clustering method for students needs to be further improved.

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