Evaluation of Faculty Teaching Effectiveness through Student Feedback Utilizing Fuzzy TOPSIS Method

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Abstract

Today, many colleges and universities have implemented a paper or web based process of how to obtain feedback from students on faculty instruction. Recent studies have confirmed what many teachers already know: that feedback in a constructive and actionable manner can dramatically enhance students' performance on a daily basis. So, students write their feedback forms on such criteria because they are by default concerned for their teachers who affect their life even more as both an educator and personal guide. The ultimate purpose of faculty performance evaluation is to discover the strengths and weaknesses in their professional growth. This specific study uses the Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) which is a special method of Multi-criteria Decision Making Problem that will improve effectiveness in ranking alternative(s).

Keywords

Multi-criteria decision making (MCDM), Fuzzy TOPSIS Method, Feedback system, Ranking, Fuzzy Positive Ideal Solution, Fuzzy Negative Ideal Solution,

1. Introduction

Over the last few decades, Multiple Criteria Decision Making (MCDM) that is multiple objective decision making has gain more popularity in terms of use and practice worldwide. The fundamental concept behind this method is relatively straightforward. It uses two points of reference, namely the positive ideal solution (PIS) and negative ideal solution (NIS) for assessment. For choose, the one closest to the PIS and farthest from the NIS. The PIS is opposite of NIS which gives all benefit criteria their maximum value and all cost criteria their minimum value.

In traditional MCMD approaches, such as the conventional TOPSIS method, the weights and ratings assigned to criteria are predetermined. However, crisp statistics often fall short in accurately representing the complexities of the real world, as human judgments, including preferences, are frequently ambiguous and difficult to quantify without some level of uncertainty. Conversely, employing linguistic evaluations in place of numerical values—by utilizing linguistic variables to assess the ratings and weights of the criteria relevant to the problem at hand—may offer a more authentic representation. The classic TOPSIS method depends on the information supplied by the expert or decision maker (DM) as precise numerical values. Nevertheless, in certain real-world scenarios, the DM may struggle to articulate the significance of the ratings of alternatives concerning specific criteria, or the expert may resort to using linguistic expressions [1].

In circumstances where the evaluations made by decision makers depend on information that is either unquantifiable, incomplete, or not readily available, alternative measurement approaches can be utilized. These approaches encompass interval numbers [2] and [3], fuzzy numbers [4], ordered fuzzy numbers [5], group decision making [6], ordered fuzzy numbers [7]. The utilization of these methodologies has been thoroughly examined across a variety of fields, with numerous instances of fuzzy TOPSIS

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applications documented in the literature. Significant areas of application include the assessment of service quality [8], comparisons [9] between companies, aggregate production planning [10], selection of facility locations [11], and large-scale nonlinear programming [12], mobile health (mHealth) applications [13], Supplier selection among others [14], Project Risk Variable Ranking [15], analysis of Multi criteria decision making [16], weights detection of multi-criteria [17] and many others
The aim of this paper is to introduce a more efficient methodology for TOPSIS-based fuzzy group decision-making (GDM) to enhance the ranking of fuzzy alternatives. The data utilized are presented in linguistic form within a feedback system. By employing the Fuzzy TOPSIS Method, we represent the feedback system and identify the optimal solution among the various options available for the given problem, as well as evaluate the performance rankings of faculties. This paper is structured into five sections: Section two outlines the fundamental components of fuzzy set theory. The TOPSIS method is detailed in Section three. The application of fuzzy TOPSIS to the problems discussed is elaborated in Section four, while Section five provides an illustrative example. The sixth section compares Fuzzy TOPSIS with other multi-criteria decision-making (MCDM) methods. The seventh section concludes our research, and the eighth section discusses future research directions.

2. Preliminaries

Here we give some of the notations which will be used frequently in the material of the present paper and some equations related to them.

2.1. Definition 1

A fuzzy set A within a given universe of discourse X includes a membership function, $\mu_A(x)$, that assigns a real number between zero and one to each element of the universal set X. This value represents the degree of membership of x in A, as defined by Zadeh [18].The membership function is presented as Equation (1)

$$\mu_A(x) : X \rightarrow \{0, 1\} \tag{1}$$

2.2. Definition 2

A fuzzy set A is consider convex if and only if for all $x1$ and $x2$ in X. The convex fuzzy set is presented as Equation (2)

$$\mu_A(\lambda x_1 + (1 - \lambda)x_2) \geq min(\mu_A(x_1), \mu_A(x_2)) \tag{2}$$

Where $\lambda \in [0, 1]$

2.3. Definition 3

A fuzzy set A consider normal fuzzy set is presented as Equation (3)

$$\exists x \in X : \mu_A(x) = 1 \tag{3}$$

2.4. Definition 4

The λ cut of fuzzy number $\tilde{n}$ is defined as Equation (4)

$$\tilde{n}^\alpha = \{x_i : \mu_{\tilde{n}}(x_i) \geq \alpha, x_i \in X\} \tag{4}$$

$\tilde{n}^\alpha$, as defined in Equation (4), represents a non-empty, bounded closed interval that lies within X. This interval can be denoted as $\tilde{n}^\alpha = [\tilde{n_1}^\alpha, \tilde{n_2}^\alpha]$, where $\tilde{n_1}^\alpha$ and $\tilde{n_2}^\alpha$ represent the lower and upper bounds of the closed interval, respectively, as defined by Zimmermann [19].

2.5. Definition 5

A triangular fuzzy number $\tilde{n}$ consider by a triplet(n_1, n_2, n_3), then the membership function $\mu_{\tilde{n}}(x)$ is defined as Equation (5):

$$Y\mu_{\tilde{X}} = \begin{cases} \frac{x-n_1}{n_2-n_1}, & \text{if} n_1 \leq x \leq n_2, \\ \frac{x-n_3}{n_2-n_3}, & \text{if} n_2 \leq x \leq n_3, \\ 0, & \text{otherwise.} \end{cases} \tag{5}$$

2.6. Definition 6

IF $\tilde{n}$ is a triangular fuzzy number and $\tilde{n}_l^{\alpha}$ and $\tilde{n}_2^{\alpha}$, then $\tilde{n}$ is called a normalized positive fuzzy number.

2.7. Definition 7

Zadeh [18] defined linguistic variables whose values are words or sentences in a natural language. In general sense, when the problems encountered are so sophisticated or have such vague/fuzzy definitions that they cannot be expressed in more precise languages such as for example mathematized forms, the idea of linguistic variable is quite handy. One of the many linguistic variables is weight, which can have fuzzy numbers in very low, low, medium, high and very high value.

3. TOPSIS Method

Hwang and Yoon (1981) developed the TOPSIS method, which assigns a ranking to the alternatives based on their separations from both the ideal and negative ideal solutions. The best alternative has not only the least Euclidean distance, but also the greatest distance in the negative ideal solution. Hence in a positive solution, one strived at arranging a solution that has maximum gain at lesser cost. On the other hand, negative solution is centered on the pains and tries to minimize gains [20]. Six stages systems are designed to provide level of the TOPSIS approach:

- Compute the normalized decision matrix as Equation (6).

$$r_{ij} = x_{ij}\sqrt{\sum_{i-1}^{m} x_{ij}^2}, i = 1, 2, \ldots, m \text{ and } j = 1, 2, \ldots, n \tag{6}$$

- Establish the weighted normalized decision matrix as Equation (7).

$$\upsilon_{ij} = r_{ij} \times \omega_j i = 1, 2, \ldots, m \text{ and } j = 1, 2, \ldots, n \tag{7}$$

  Where, ω_j is the weight of the j_{th} criterion or attribute and $\sum_{j=1}^{n} \omega_j = 1$.
- Compute the positive ideal (A^*) as Equation (8)and negative (A^-) ideal solutions as Equation (9)

$$A^* = \{(max_i^{\upsilon_{ij}} | j \in C_b), (min_i^{\upsilon_{ij}} | j \in C_c)\} = \{\upsilon_j^* | j = 1, 2, \cdots, m\} \tag{8}$$

$$A^- = \{(min_i^{\upsilon_{ij}} | j \in C_b), (max_i^{\upsilon_{ij}} | j \in C_c)\} = \{\upsilon_j^- | j = 1, 2, \cdots, m\} \tag{9}$$

- The distance are computed by calculating the Euclidean distance across multiple dimensions. The specific separation measures for each alternative, in relation to both the A^* as Equation (10) and the A^- as Equation (11), are outlined as following way:

$$S_i^* = \sqrt{\sum_{j=1}^{m} (\upsilon_{ij} - \upsilon_j^*)}, j = 1, 2, \cdots, m \tag{10}$$

$$S_i^- = \sqrt{\sum_{j=1}^{m}(v_{ij} - v_j^-)}, j = 1, 2, \cdots, m \tag{11}$$

- Determine the relative proximity to the ideal solution S.
- The proximity of the alternative A_i with respect to A^* is characterized in the following way and ranking the preference order as Equation (12).

$$RC_i^* = \sqrt{\frac{S_i^-}{S_i^* + S_i^-}}, i = 1, 2, \cdots, m \tag{12}$$

4. Fuzzy TOPSIS Method

This analysis of the various alternatives utilizes the Technique for Order Preference by Similarity to Ideal Situation (TOPSIS), which includes methods such as the fuzzy TOPSIS technique. This approach employs criteria weights and ratings for alternatives expressed in linguistic variables that are converted into Triangular Fuzzy Numbers [21]. According to this methodology, the most favored alternatives should be positioned as close as possible to the Fuzzy Positive Ideal Solution (FPIS) while being situated as far away as possible from the Fuzzy Negative Ideal Solution (FNIS).

Fuzzy TOPSIS method steps are provided below and the techniques of weights of criteria and ranking of alternatives [22]:

Step 1: Create the classified diagram.

Step 2: Implement the data scaling process according to the defined criteria and alternatives. The linguistic variables utilized by the decision-maker(s) for evaluating the alternatives are outlined in Table 1, while the allocation of weights assigned to the criteria is presented in Table 2.

Table 1
Linguistic variables and Triangular Fuzzy Numbers for the criteria

Linguistic variables	TFNs
Indeed-superior(A1)	(8,9,10)
Superior(A2)	(7,8,9)
Above-average(A3)	(4,5,6)
Average(A4)	(3,4,5)
Below-average(A5)	(2,3,4)
Poor(A6)	(1,2,3)
Very-poor(A7)	(1,1,1)

Table 2
Linguistic variables and TFNs for alternative weights

Linguistic variables	TFNs
Indeed-critical (W1)	(8,9,10)
Rather-critical(W2)	(7,8,9)
Very-important(W3)	(4,5,6)
Important(W4)	(3,4,5)
Rather-important(W5)	(2,3,4)

Step 3: Calculate the total fuzzy weight of each of the criterion, $\tilde{w}_j$ of the k_{th} decision maker described as Equation (13) and as Equation(14):

$$\tilde{w}_j = (w_{j1}, w_{j2}, w_{j3}) \tag{13}$$

Where,

$$W_{j1} = min_k\{W_{j1}^k\} \quad W_{j2} = \frac{1}{K}\sum_{k=1}^{K} W_{j2}^k \quad W_{j3} = max_k\{W_{j3}^k\} \tag{14}$$

where, $j = 1, 2, \cdots, n^{th}$ criteria.

Step 4: To construct the fuzzy decision matrix as Equation (15), represented as $\tilde{D}$, which includes the alternatives, i, and the criteria, j, the subsequent elements will be necessary .

$$\tilde{D} = \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix} \tag{15}$$

where, $i = 1, 2, \ldots, m$ (alternatives), $j = 1, 2, \ldots, n$ (criteria).

Let $\tilde{x}_{ij}$ represent the associated fuzzy evaluations of alternative i with respect to each criterion j, as determined by a group of K decision-makers. The calculation of $\tilde{x}_{ij}$ is performed in the following manner as Equations (16)-(18):

$$\tilde{x}_j = (a_{ij}, b_{ij}, c_{ij}) \tag{16}$$

where,

$$\begin{gathered} a_{ij} = min_k\{a_{ij}^k\} \\ b_{ij} = \frac{1}{K}\sum_{k=1}^{K} b_{ij}^k \\ c_{ij} = max_k\{c_{ij}^k\} \end{gathered} \tag{17}$$

$$\tilde{x}_{ij}^k = (a_{ij}^k, b_{ij}^k, c_{ij}^k) \tag{18}$$

Step 5: Normalize the fuzzy decision matrix using Equations (19)- (20):

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{b_j^*}, \frac{c_{ij}}{c_j^*}\right) \tag{19}$$

and $c_j^* = max_i\{c_{ij}\}$ (benefit criteria).

$$\tilde{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right) \tag{20}$$

and $a_j^- = min_i\{a_{ij}\}$ (cost criteria).

Step 6: Compute the weighted normalized fuzzy decision matrix, $\tilde{V}$as Equation (21), as presented below, by multiplying $\tilde{r}_{ij}$, with w_j, in the following manner:

$$\tilde{V} = [\tilde{v}_{ij}]_{mn} \tag{21}$$

where, $i = 1, 2 \cdots, m$ alternatives , $j = 1, 2, \ldots, n$ criteria, $\tilde{v}_{ij} = \tilde{r}_{ij} \times \tilde{w}_{ij}$.

Step 7: Compute the FPIS, A^* and FNIS, A^- using Equations (22)-(23):

$$\tilde{A} = (\tilde{v}_1^*, \tilde{v}_2^*, \tilde{v}_3^*), \text{ where } \tilde{v}_1^* = max_i\{v_{ij3}\} \tag{22}$$

$$\tilde{A} = (\tilde{v}_1^-, \tilde{v}_2^-, \tilde{v}_3^-), \text{ where } \tilde{v}_1^- = min_i\{v_{ij3}\} \tag{23}$$

Step 8: Compute the distance of each alternative, (d_i^*, d_i^-) where $i = 1, 2, 3, \cdots, m$ from the FPIS and FNIS by applying the Equations (24)-(26) below:

$$d_i^* = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^*) \tag{24}$$

$$d_i^- = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^-) \tag{25}$$

$$d(\tilde{a}, \tilde{b}) = \sqrt{\frac{1}{3}[(a_1 - a_2)^2 + (b_1 - b_2)^2 + (c_1 - c_2)^2]} \tag{26}$$

Step 9: Compute the closeness coefficient, CC_i using Equation (27):

$$CC_i = \frac{d_i^-}{d_i^- + d_i^*} \tag{27}$$

where,$i = 1, 2, 3, \cdots, m$.

Step 10: Arrange the alternatives based on the calculated values of the closeness coefficient to the ideal solution in descending order. It can be understood that the optimal alternative, characterized by the highest CC_i value, is nearer to the FPIS and more distant from the FNIS. Figure 1 shows the visual representation of the Fuzzy TOPSIS process.

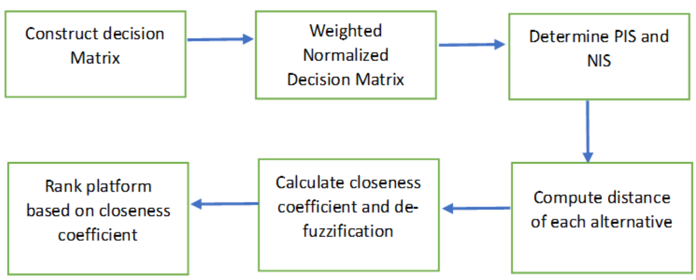

Figure 1: Fuzzy TOPSIS Steps

5. Illustrative Example

Today, feedback system is very important for many institutions. This system can help improve a teacher's performance, behavior during the class, methods of teaching as well as style of teaching among other things. The feedback system has many items such as "timeliness," "communication skill," "control of the class," and many others. Importance of performance is always an influential factor on a venture example if a factor has extremely high performance. Now we define secondary linguistic values for performance factors which are described in Table 1 and for secondary linguistic values of significance factor described in T. This paper will employ the fuzzy TOPSIS approach to present an empirical application for the evaluation of the teaching effect of college. Hence in this paper, three expert decision makers, namely $D_i(i = 1, 2, 3, 4, 5)$ have been selected to complete the feedback form to assess the faculties' teaching performance where five faculties, $F_i(i = 1, 2, 3, 4, 5)$ are involved and some criteria are used. Twelve benefit criteria are considered: Twelve benefit criteria are considered:
C1. Timeliness
C2. Attempt to complete syllabus
C3. Whether well performed and enough Knowledgeable about the topic
C4. Communication skill
C5. Control of the class
C6. Involvement in doubt clearance
C7. When attending the class, present the material in a clear manner
C8. Daily reminder of class assignments and adherence to lecture plan
C9. Proper experimental guidance
C10. Responsibility
C11. Teacher is approachable outside the class
C12. assessment is a guide and a well-wisher
In this paper, the assessments conducted by the decision makers concerning the criteria are presented in Table 3for Decision Maker (D1), Table 4 for Decision Maker (D2) and Table 5 for Decision Maker (D1) so on, which are further clarified by Figures 2- 4 through the use of line charts. Furthermore, the linguistic variables related to the criteria are converted into Triangular Fuzzy Numbers (TFNs) utilizing the scales, as illustrated in Equation (16).

Table 3
Decision Maker (D1)

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
F1	(7 8 9)	(7 8 9)	(7 8 9)	(8 9 10)	(7 8 9)	(4 5 6)	(3 4 5)	(7 8 9)	(4 5 6)	(7 8 9)	(7 8 9)	(8 9 10)
F2	(3 4 5)	(2 3 4)	(3 4 5)	(3 4 5)	(2 3 4)	(3 4 5)	(4 5 6)	(2 3 4)	(3 4 5)	(3 4 5)	(2 3 4)	(3 4 5)
F3	(8 9 10)	(7 8 9)	(8 9 10)	(3 4 5)	(4 5 6)	(3 4 5)	(7 8 9)	(8 9 10)	(7 8 9)	(7 8 9)	(8 9 10)	(7 8 9)
F4	(3 4 5)	(3 4 5)	(1 2 3)	(1 2 3)	(3 4 5)	(3 4 5)	(4 5 6)	(2 3 4)	(4 5 6)	(3 4 5)	(1 2 3)	(3 4 5)
F5	(2 3 4)	(3 4 5)	(2 3 4)	(1 2 3)	(4 5 6)	(1 2 3)	(1 2 3)	(1 1 1)	(1 2 3)	(3 4 5)	(4 5 6)	(4 5 6)

Table 4
Decision Maker (D2)

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
F1	(7 8 9)	(7 8 9)	(8 9 10)	(8 9 10)	(7 8 9)	(8 9 10)	(7 8 9)	(7 8 9)	(7 8 9)	(3 4 5)	(7 8 9)	(3 4 5)
F2	(2 3 4)	(2 3 4)	(3 4 5)	(3 4 5)	(3 4 5)	(3 4 5)	(2 3 4)	(3 4 5)	(2 3 4)	(4 5 6)	(3 4 5)	(4 5 6)
F3	(7 8 9)	(4 5 6)	(3 4 5)	(7 8 9)	(8 9 10)	(7 8 9)	(8 9 10)	(7 8 9)	(7 8 9)	(7 8 9)	(7 8 9)	(7 8 9)
F4	(3 4 5)	(3 4 5)	(1 2 3)	(4 5 6)	(3 4 5)	(3 4 5)	(1 2 3)	(3 4 5)	(3 4 5)	(4 5 6)	(3 4 5)	(4 5 6)
F5	(3 4 5)	(4 5 6)	(1 2 3)	(1 2 3)	(2 3 4)	(4 5 6)	(4 5 6)	(3 4 5)	(3 4 5)	(1 2 3)	(3 4 5)	(1 2 3)

Table 5
Decision Maker (D3)

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
F1	(3 4 5)	(3 4 5)	(7 8 9)	(8 9 10)	(4 5 6)	(7 8 9)	(7 8 9)	(7 8 9)	(7 8 9)	(7 8 9)	(8 9 10)	(7 8 9)
F2	(4 5 6)	(4 5 6)	(3 4 5)	(3 4 5)	(3 4 5)	(2 3 4)	(3 4 5)	(2 3 4)	(2 3 4)	(3 4 5)	(3 4 5)	(2 3 4)
F3	(7 8 9)	(7 8 9)	(7 8 9)	(7 8 9)	(7 8 9)	(4 5 6)	(7 8 9)	(7 8 9)	(8 9 10)	(8 9 10)	(3 4 5)	(7 8 9)
F4	(4 5 6)	(4 5 6)	(3 4 5)	(3 4 5)	(4 5 6)	(3 4 5)	(3 4 5)	(3 4 5)	(1 2 3)	(3 4 5)	(1 2 3)	(3 4 5)
F5	(1 2 3)	(1 2 3)	(3 4 5)	(4 5 6)	(1 2 3)	(4 5 6)	(3 4 5)	(3 4 5)	(4 5 6)	(2 3 4)	(1 2 3)	(3 4 5)

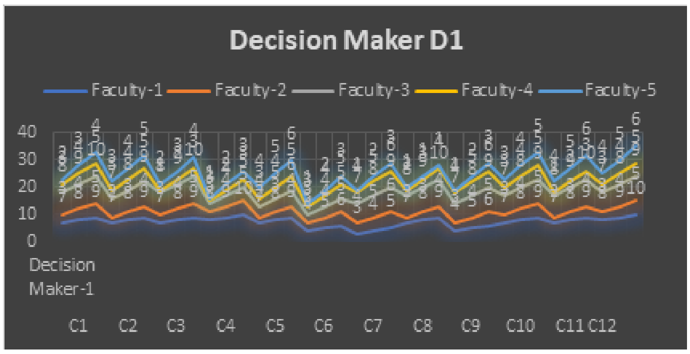

Figure 2: Line chart of Decision Maker 1

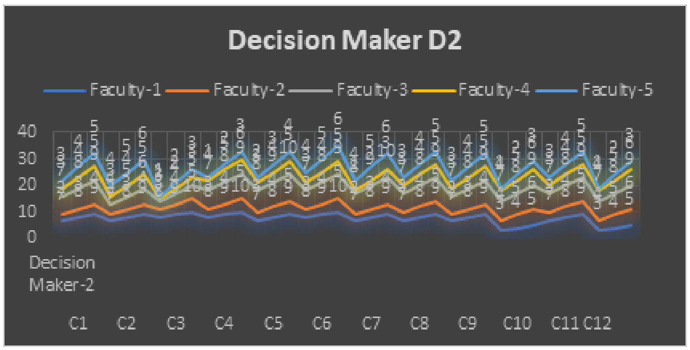

Figure 3: Line chart of Decision Maker 2

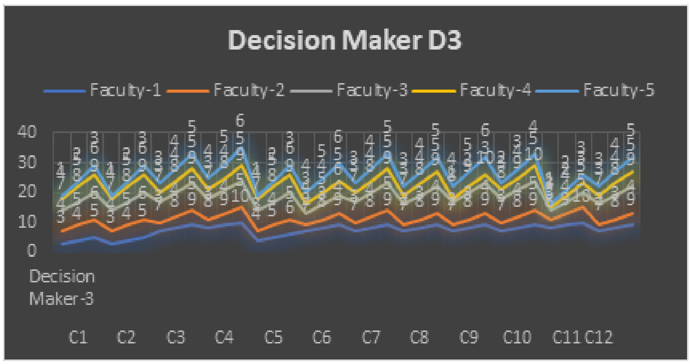

Figure 4: Line chart of Decision Maker 3

5.1. Ranking the Alternatives

Using combined decision matrix with aggregated fuzzy weights of importance criteria w_j is calculated by Equation (18).

Table 6
Combined Decision Matrix

	W3	W1	W3	W3	W4	W5	W4	W1	W2	W4	W1	W2
F1	(3,6.7,9)	(3,6.7,9)	(7,8.3,10)	(8,9,10)	(4,7,9)	(4,7.3,10)	(3,6.7,9)	(7,8,9)	(4,7,9)	(3,6.7,9)	(7,8.3,10)	(3,7,10)
F2	(2,4,6)	(2,3.6,6)	(3,4,5)	(3,4,5)	(2,3.6,5)	(2,3.7,5)	(2,4,6)	(2,3.3,5)	(2,3.3,5)	(3,4.3,6)	(2,3.7,5)	(2,4,6)
F3	(7,8.3,10)	(4,7,9)	(3,7,10)	(3,6.6,9)	(4,7.3,10)	(3,5.6,9)	(7,8.3,10)	(7,8.3,10)	(7,8.3,10)	(7,8.3,10)	(3,7,10)	(7,8,9)
F4	(3,4.3,6)	(3,4.3,6)	(1,2.7,5)	(1,3.7,6)	(3,4.3,6)	(3,4,5)	(1,3.7,6)	(2,3.7,5)	(1,3.7, 6)	(3,4.3,6)	(1, 2.6,5)	(3,4.3,6)
F5	(1,3,5)	(1,3.7,6)	(1,3,5)	(1,3,6)	(1,3.3,6)	(1,4,6)	(1,3.7,6)	(1,3,5)	(1,3.7,6)	(1,3,5)	(1,3.7,6)	(1,3.7,6)

Equation(19)-(20), calculated the normalized decision matrix which are shown in Table 7.

Table 7
Normalized Fuzzy Decision Matrix

	W3	W1	W3	W3	W4	W5	W4	W1	W2	W4	W1	W2
F1	(0.3,0.7,0.9)	(0.3,0.7,1)	(0.7,0.8,1)	(0.8,0.9,1)	(0.4,0.7,0.9)	(0.4,0.7,1)	(0.3,0.6,0.9)	(0.7,0.8,0.9)	(0.4, 0.7,0.9)	(0.3,0.6,0.9)	(0.7,0.8,1)	(0.3,0.7,1)
F2	(0.2,0.4,0.6)	(0.2,0.4,0.6)	(0.3,0.4,0.5)	(0.3,0.4,0.5)	(0.2,0.3,0.5)	(0.2,0.3,0.5)	(0.2,0.4,0.6)	(0.2,0.3,0.5)	(0.2,0.3,0.5)	(0.3,0.4,0.6)	(0.2,0.3,0.5)	(0.2,0.4,0.6)
F3	(0.7,0.8,1)	(0.4,0.7,1)	(0.3,0.7,1)	(0.3,0.6,0.9)	(0.4,0.7,1)	(0.3,0.5,0.9)	(0.7,0.8,1)	(0.7,0.8,1)	(0.7,0.83,1)	(0.7,0.8,1)	(0.3,0.7,1)	(0.7,0.8,0.9)
F4	(0.3,0.4,0.6)	(0.3,0.4,0.6)	(0.1,0.27,0.5)	(0.1,0.3,0.6)	(0.3,0.4,0.6)	(0.3,0.4,0.5)	(0.1,0.37,0.6)	(0.2,0.37,0.5)	(0.1,0.37,0.6)	(0.3, 0.4,0.6)	(0.1,0.27,0.5)	(0.3,0.4,0.6)
F5	(0.1,0.3,0.5)	(0.1,0.4,0.67)	(0.1,0.3,0.5)	(0.1,0.3,0.6)	(0.1,0.3,0.6)	(0.1,0.4,0.6)	(0.1,0.3,0.6)	(0.1,0.3,0.5)	(0.1,0.3,0.6)	(0.1,0.3,0.5)	(0.1,0.3,0.6)	(0.1, 0.3,0.6)

Equation (21)-(23) compute V matrix which are shown in Table 8.

Table 8
Weighted Normalized Fuzzy Decision Matrix

	W3	W1	W3	W3	W4	W5	W4	W1	W2	W4	W1	W2
F1	(0.12,3.3,5.4)	(2.6,6.6,10)	(2.8,4.1,6)	(3.2,4.5,6)	(1.2,2.8,4.5)	(0.8,2.2,4)	(0.9,2.6,4.5)	(5.6,7.2,9)	(2.8,5.6, 8.1)	(0.9,2.67,4.5)	(5.6,7.5,10)	(2.1,5.6,9)
F2	(0.08,2,3.6)	(1.7,3.6,6.6)	(1.2,2,3)	(1.2,2,3)	(0.6,1.4,2.5)	(0.4,1.1,2)	(0.6,1.6,3)	(1.6,3,5)	(1.4,0.03,4.5)	(0.9,1.7,3)	(1.6,3.3,5)	(0.02,3.2,5.4)
F3	(0.2,4.1,6)	(3.5,7,10)	(1.2,3.5,6)	(1.2,3.3,5.4)	(1.2,2.9,5)	(0.6,1.7,3.6)	(2.1,3.3,5)	(5.6,7.5,10)	(4.9,0.08,9)	(2.1,3.3,5)	(2.4,6.3,10)	(0.07,6.4,8.1)
F4	(0.1,2.1,3.6)	(2.6,4.3,6.6)	(0.4,1.3,3)	(0.4,1.8,3.6)	(0.9,1.7,3)	(0.6,1.2,2)	(0.3,1.4,3)	(1.6,3.3,5)	(0.7,0.03,5.4)	(0.9,1.7,3)	(0.8,2.4,5)	(0.03,3.4,5.4)
F5	(0.04,1.5,3)	(0.8,3.6,6.6)	(0.4,1.5,3)	(0.4,1.5,3.6)	(0.3,1.3,3)	(0.2,1.2,2.4)	(0.3,1.4,3)	(0.8,2.7,5)	(0.7,0.03, 5.4)	(0.3,1.2,2.5)	(0.8,3.3,6)	(0.01,2.9,5.4)
A*	(0.2,4.1,6)	(3.5,7,10)	(2.8,4.1,6)	(3.2,4.5,6)	(1.2,2.9,5)	(0.8,2.2,4)	(2.1,3.3,5)	(5.6,7.5,10)	(4.9,5.6,9)	(2.1, 3.3,5)	(5.6,7.5,10)	(2.1, 6.4, 9)
A-	(0.04,1.5,3)	(0.8,3.6,6.6)	(0.4,1.3,3)	(0.4,1.5,3)	(0.3,1.3,2.5)	(0.2,1.1,2)	(0.3,1.4,3)	(0.8,2.7,5)	(0.7,0.03,4.5)	(0.3,1.2,2.5)	(0.8,2.4,5)	(0.01,2.9,5.4)

Equation (24)- (26) show the process of measuring distance of each of the alternative of FPIS and FNIS. In Table 8, the alternatives are organized according to their closeness coefficients in relation to the ideal solution. The most favorable alternative is determined as the one that is the farthest from the FNIS and nearest to the FPIS, distinguished by a higher CC_i score derived from Equation (27), as shown in Table 9. Furthermore, Figure 5 depicts the ranking of the alternatives using a 3D pie chart.

Table 9
Rankings of the alternatives

RANK	CC_i	FACULTY
1	0.853677381	F1
3	0.241583701	F2
2	0.756295088	F3
4	0.235655207	F4
5	0.197371895	F5

6. Comparison with other Methods

The Analytic Hierarchy Process (AHP) [23], Data Envelopment Analysis (DEA) [24], and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [25] are well-established multi-criteria decision-making (MCDM) techniques that are extensively applied in diverse domains, including supply chain management, healthcare, and environmental sustainability.
AHP is a methodical approach that enables decision-makers to create a hierarchical model of complex

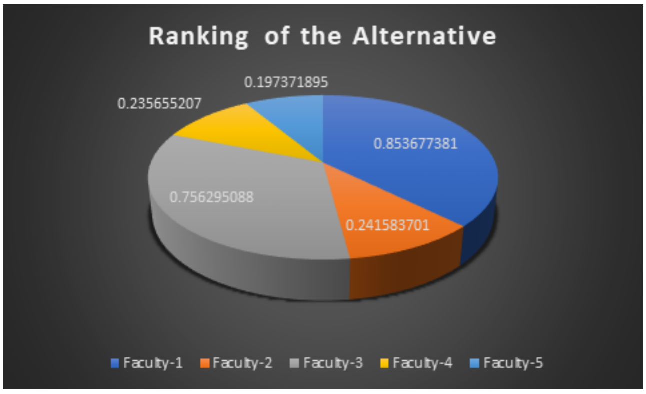

Figure 5: Ranking of the Alternative

issues. It entails breaking down an issue into its component elements so that criteria and options can be compared pairwise. By translating subjective assessments into numerical values that are then combined to create priority weights, AHP makes it easier to quantify subjective assessments. This approach is appropriate for supplier selection and project prioritization.
On the other hand, DEA is a non-parametric technique that compares the input-output ratios of decision-making units (DMUs) to assess their efficiency. In order to identify best practices and benchmark, DEA operates under the premise that the DMUs are operating in a similar environment. It is especially useful in situations when there are several inputs and outputs, such measuring the effectiveness of production processes or the performance of healthcare facilities.
The idea of the geometric distance from an ideal solution, however, is the foundation of TOPSIS. It takes into account the worst-case situation and evaluates options according to how close they are to the ideal solution. Because TOPSIS clearly ranks solutions according to their performance, it is especially helpful when decision-makers need to compare several options to a set of criteria.
By incorporating fuzzy logic into the conventional TOPSIS framework, fuzzy TOPSIS overcomes these drawbacks. Decision-makers can now communicate their preferences in a more nuanced way thanks to this adaption, which permits the portrayal of ambiguity and uncertainty in the decision-making process. A ranking of options can be obtained by processing fuzzy integers that reflect criteria weights and performance ratings in fuzzy TOPSIS.
While comparing them, DEA is excellent at assessing efficiency across a variety of inputs and outputs, AHP is useful for combining subjective assessments and qualitative criteria. TOPSIS is appropriate for situations needing prompt selections based on a number of factors since it provides a simple method for evaluating possibilities. Fuzzy TOPSIS has a major edge in managing ambiguity and uncertainty, which makes it especially helpful in complicated decision-making situations where qualitative considerations are important. Table 10 shows the ranking comparison of the alternatives of the discussed methods for the feedback system.

Table 10
Comparison of the results with other methods

RANK	FACULTTY
Fuzzy TOPSIS	F1 > F3 > F2 > F4 > F5
AHP	F1 > F3 > F2 > F5> F4
Traditional TOPSIS	F1 > F3 > F2 > F5> F4
DEA	F1 > F3 > F2 > F5> F4

7. Conclusion

In this study, the implementation of Fuzzy TOPSIS utilized real-world data pertaining to the evaluation of faculty selection in an academic institution. The feedback regarding faculty teaching effectiveness tends to be general and ambiguous, often lacking quantifiable data from students, which leads to a reliance on the opinions of decision-makers. The said method effectively transforms the linguistic variables representing the preferences of decision-makers into Triangular Fuzzy Numbers (TFNs). This approach proves advantageous in addressing these issues, as it allows for the measurement of criterion weights and the assessment of all options relative to each criterion. To test the hypothesis that F1 > F3 > F2 > F4 > F5, the results indicated a discernible difference in the evaluation of the alternatives. Consequently, F1 emerged as the most preferred option, while F5 was identified as the least preferred candidate. Therefore, the study's objective of evaluating criterion weights and decision-making options for conducting Fuzzy TOPSIS analysis in faculty selection has been clearly articulated

8. Future Scope

In our upcoming initiatives, the established model and algorithm will play a crucial role in tackling a range of real-world multi-attribute group decision-making (MAGDM) issues, employing supplementary aggregation operators including the Einstein geometric aggregation operator, Bonferroni mean aggregation operator, and Yager ordered weighted average (OWA) aggregation operators.

9. Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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