A Group Decision Making Problem Involving Fuzzy TOPSIS Method

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Abstract Selection is a process to find out the best alternative solution result using the given alternatives, criteria and experts. The purpose of this manuscript is to development of fuzzy technique to group fuzzy technique method through FTOPSIS method. We introduce a literature survey in different models of fuzzy and that have been applied the field of decision making. In the multi-criteria decision technique, fuzzy TOPSIS is proposed for selection of four different projects by fuzzy TOPSIS software. Lastly, we determine the best project using group fuzzy TOPSIS methodology. To illustrate the sequel of the group ideal solution and have defend our replica to be structured and vigorous.

Keywords MCDM · Fuzzy TOPSIS · Group FTOPSIS · Relative closeness matrix

1 Introduction

Decision making (DM) is a process of finding solution in our day-to-day life. In every step, we are taking the decision by the help of human being or any technique or by soft computing process. In this paper, we are taking the decision through multi-criteria decision-making (MCDM) problems or multi-attribute decision-making (MADM) [1] using fuzzy technique for order performance by similarity to positive ideal solutions (FTOPSIS) techniques. This process is to define the ranking of all possible alternatives with respect to the goal and more than one criteria. There are several real-world applications of MCDM method; data are usually vague, ambiguous and/or unpredictable. The MCDM [2] problems credible and are excessively applied in many domains, such as different engineering sciences, management, mathematical sciences, economics, medical sciences and soon. The DM has to select, assess or rank these alternatives according to the weights of the criteria. The important branch of subject operation research is the MCDM technique [3–5] used in the last five decades.

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In the real-life situations, the problems of DM are subjected to objectives, constraints and their consequences that are not meticulously known. The new decision theory is known today as fuzzy multi-criteria decision-making (FMCDM) [6, 7] is the condensation allying MCDM [8] and fuzzy set theory [9], where the DM models are deal with insufficient and undetermined intelligence and evidence. Many researchers have been preoccupied by decision-making (DM) problems [10–13] in fuzzy environments. To describe the subjective judgment of a DM in a quantitative manner, fuzzy numbers (FNs) most often used in triangular FN, trapezoidal FN.

In the TOPSIS method, the best alternative is one which is nearest to the PIS and at maximum length from the NIS. In the PIS, the benefit criteria get maximized and the cost criteria get minimized. In the NIS, the cost criteria get maximized and the benefit criteria get minimized. As a practical application of TOPSIS method, we can see [11, 12]. In this situation where the available information is vauge, imprecise or uncertain, it is quite difficult to precisely asses the alternatives with respect to the criteria. The rating of every one alternative with respect to every one criterion can be described by fuzzy numbers [3].

The TOPSIS method has been broadened to handle MCDM with an unsettled DM with consequence in fuzzy TOPSIS [11–13], which has fortunately been used to solve different MCDM problems [13–18]. In this way, we obtain extensions of the TOPSIS method under fuzzy environment, i.e., fuzzy TOPSIS. The remnants of this paper are assembled into different segments having backdrop enlightenment about research methodology. In this paper, we organized as follows. In Section 2, we outlined the basic concepts of fuzzy set, fuzzy membership function, triangular fuzzy numbers, the TOPSIS method and FTOPSIS method. In Section 3, we suggested research methodology and proposed algorithm. Section 4 presents empirical studies and Sect. 5 concludes the study.

2 Basic Concepts

In this section, first, we briefly introduce some definitions and concepts related to fuzzy set, fuzzy membership function, triangular fuzzy numbers (TFN) and algorithm of TOPSIS method, fuzzy TOPSIS method by group decision-making method.

2.1 Definitions

Definition 1 (Fuzzy set). Let U be an universe of objects with an $u \in U$. A fuzzy set $\overline{A}$ in U is characterized by $\mu_{\overline{A}}(u)$ membership function $u \in [0, 1]$ representing the grade of membership function of u in $\overline{A}$. Then.

$$\overline{A} = \left\{ \left(u, \mu_{\overline{A}}(u)\right) : u \in U \right\}, \quad \text{where} \quad \mu_{\overline{A}}(u) : U \to [0, 1] \tag{1}$$

Definition 2 (TFN). If $\overline{Tr}$ is a TFN and $\left[\overline{t_n}\right]_\beta^l > 0$ and $\left[\overline{t_n}\right]_\beta^u \leq 1$ for $\beta \in (0, 1]$, so $\overline{t_n}$ is called a normalized TFN.

Definition 3 (Membership of TFN) Let $\overline{a}$ be a fuzzy number which is defined by a triplet $\overline{a} = (a_1, a_2, a_3)$. Then the membership function is denoted as $\mu_{\overline{a}}(u)$, defined by.

$$\mu_{\overline{a}}(u) = \begin{cases} 0, & u < a_1 \\ (u - a_1)\big/(a_2 - a_1), & a_2 \geq u \geq a_1 \\ (u - a_2)\big/(a_3 - a_2), & a_3 \geq u \geq a_2 \\ 0, & u < a_3 \end{cases} \tag{2}$$

Definition 4 (Operation of TFN). Let $\overline{u} = (u_1, u_2, u_3)$ and $\overline{v} = (v_1, v_2, v_3)$ be two positive TFNs, then the operation with these fuzzy numbers is demarcated as follows.

$$\overline{u}(\mp)\overline{v} = (\overline{u}_1(\mp)\overline{v}_1, \overline{u}_2(\mp)\overline{v}_2, \overline{u}_3(\mp)\overline{v}_3) \tag{3}$$

$$\overline{u}(\times)\overline{v} = (\overline{u}_1(\times)\overline{v}_1, \overline{u}_2(\times)\overline{v}_2, \overline{u}_3(\times)\overline{v}_3) \tag{4}$$

$$\overline{u}(/)\overline{v} = (\overline{u}_1(/)\overline{v}_1, \overline{u}_2(/)\overline{v}_2, \overline{u}_3(/)\overline{v}_3) \tag{5}$$

$$k\overline{v} = (kv_1, kv_2, kv_3) \tag{6}$$

Definition 5 (Distance of TFN). Let $\overline{u} = (u_1, u_2, u_3)$ and $\overline{v} = (v_1, v_2, v_3)$ be two positive TFNs, then distance is computed by.

$$d(\overline{u}, \overline{v}) = \sqrt{\frac{1}{3}\left[(u_1 - v_1)^2 + (u_1 - v_1)^2 + (u_1 - v_1)^2\right]} \tag{7}$$

Definition 6 (α-cut). The α-cut is a fuzzy set $\overline{A} \subset U$ and is defined by.

$$\left[\overline{A}\right]_\alpha = \left\{u \middle| \mu_{\overline{A}}(u) \geq \alpha\right\}, \text{ where } \alpha \in [0,\ 1] \tag{8}$$

2.2 TOPSIS Method

Step 1 Choose decision matrix D is described by $D = A_i \overset{C_j}{\underset{m\times n}{\left(u_{ij}\right)}}$, where A_i, $i = 1, \ldots, m$ are alternatives and C_j, $j = 1, \ldots, n$ are criteria, u_{ij} are original scores express the grading of the alternative A_i with respect to criteria C_j. The weight vector $w = (w_1, w_2, \ldots, w_n)$ is collected the discrete weights $w_j (j = 1, 2, \ldots, n)$ for every one criteria C_j.

Step 2 Construct normalized decision matrix N_{ij}, where $\mathrm{N}_{ij} = u_{ij} / \sqrt{\sum u_{ij}^2}$ for $i = 1, \ldots, m; \quad j = 1, \ldots, n$, where u_{ij} and N_{ij} are original and normalized matrix, respectively.

Step 3 The weighted normalized decision matrix $V_{ij} = w_j \mathrm{N}_{ij}$, where w_j is the weight for jth criteria and $\sum w_j = 1$.

Step 4 The PIS and NIS are $\mathrm{A}^+ = \left(v_1^+, v_2^+, \ldots, v_n^+\right)$ and $\mathrm{A}^- = \left(v_1^-, v_2^-, \ldots, v_n^-\right)$, where $v_j^+ = \{\max_i V_{ij} | j \in J_1;\ \min_i V_{ij} | j \in J_2\}$ and $v_j^- = \{\min_i V_{ij} | j \in J_1;\ \max_i V_{ij} | j \in J_2\}$.

where J_1 represent benefit criteria and J_2 represent cost criteria.

Step 5 Compute the Euclidean lengths from the PIS A^+ and NIS A^- solutions for every one alternatives A_i:

$$\delta_i^+ = \sqrt{\sum_j \left(\Delta_{ij}^+\right)^2} \quad \text{and} \quad \delta_i^- = \sqrt{\sum_j \left(\Delta_{ij}^-\right)^2}$$

where $\Delta_{ij}^+ = \left(v_j^+ - V_{ij}\right)$ and $\Delta_{ij}^- = \left(v_j^- - V_{ij}\right)$ with $i = 1, \ldots, m$

Step 6 Compute the relative closeness Ω_i for every one alternative A_i with respect to PIS A^+ as given by $\Omega_i = \delta_i^- / \left(\delta_i^- + \delta_i^+\right)$, where $i = 1, \ldots, m$.

2.3 Fuzzy TOPSIS Method

Suppose there exists m possible alternatives $u_1, u_2, ..., u_m$ for which the decision maker (DM) has to choose on the basis on n attributes $C_1, C_2, ..., C_n$ both qualitative and quantitative A_i on a attribute C_j given by the decision maker is a triangular fuzzy number $\overline{u}_{ij}$, where $i = 1, 2, ..., m, j = 1, 2, ..., n$. The MADM problem can be expressed in the matrix form as

$$\overline{F} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{pmatrix} \overline{u}_{11} & \overline{u}_{12} & \cdots & \overline{u}_{1n} \\ \overline{u}_{21} & \overline{u}_{22} & \cdots & \overline{u}_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \overline{u}_{m1} & \overline{u}_{m2} & \cdots & \overline{u}_{mn} \end{pmatrix} \end{array}$$

2.3.1 Algorithm

Step 1. Identify the evaluation criteria which may be expressed in linguistic variables.
Step 2. Calculate every one alternatives in form of criteria.
Step 3. Identify the weight of the criteria which may also be fuzzy in nature.
Step 4. Establish the fuzzy decision matrix $\overline{F}$. In this matrix, every $\overline{u}_{ij}$ is a triangular fuzzy number $\overline{u}_{ij} = \left(u_{ij}, \alpha_{ij}, \beta_{ij}\right)$.
Step 5. Establish the normalized fuzzy decision matrix $\tilde{N}_{ij}$

For every fuzzy number $\overline{u}_{ij} = \left(u_{ij}, \alpha_{ij}, \beta_{ij}\right)$, we establish the set of α-cut as $\overline{u}_{ij} = \left(\left[\overline{u}_{ij}\right]_{\alpha}^{l}, \left[\overline{u}_{ij}\right]_{\alpha}^{u}\right)$, $\alpha \in [0, 1]$. Every one fuzzy number $\overline{u}_{ij}$ is transformed into an interval. Now this interval is transformed into normalized interval

$$\left[\tilde{n}_{ij}\right]_{\alpha}^{l} = \left[\overline{u}_{ij}\right]_{\alpha}^{l} / \sum_{i=1}^{m}\left[\left(\left[\overline{u}_{ij}\right]_{\alpha}^{l}\right)^{2} + \left(\left[\overline{u}_{ij}\right]_{\alpha}^{u}\right)^{2}\right], \quad j = 1, 2, ..., n$$

$$\left[\tilde{n}_{ij}\right]_{\alpha}^{u} = \left[\overline{u}_{ij}\right]_{\alpha}^{u} / \sum_{i=1}^{m}\left[\left(\left[\overline{u}_{ij}\right]_{\alpha}^{l}\right)^{2} + \left(\left[\overline{u}_{ij}\right]_{\alpha}^{u}\right)^{2}\right], \quad j = 1, 2, ..., n$$

Now $\left(\left[\overline{n}_{ij}\right]_{\alpha}^{l}, \left[\overline{n}_{ij}\right]_{\alpha}^{u}\right)$ is the normalized interval of $\left(\left[\overline{u}_{ij}\right]_{\alpha}^{l}, \left[\overline{u}_{ij}\right]_{\alpha}^{u}\right)$ which is transformed into a fuzzy number $\overline{N}_{ij} = \left(n_{ij}, a_{ij}, b_{ij}\right)$. According to setting the value of $\alpha = 1$, we have $\left[\overline{n}_{ij}\right]_{\alpha=1}^{l} = \left[\overline{n}_{ij}\right]_{\alpha=1}^{u} = n_{ij}$ and setting the value $\alpha = 0$, we have $\left[\overline{n}_{ij}\right]_{\alpha=1}^{l} = n_{ij} - a_{ij}$ and $\left[\overline{n}_{ij}\right]_{\alpha=1}^{u} = n_{ij} + b_{ij}$ then $a_{ij} = n_{ij} - \left[\tilde{n}_{ij}\right]_{\alpha=0}^{l}$ and $b_{ij} = \left[\overline{n}_{ij}\right]_{\alpha=0}^{u} - n_{ij}$. Now $\overline{N}_{ij} = \left(n_{ij}, a_{ij}, b_{ij}\right)$ is the fuzzy number of the normalized interval $\left(\left[\overline{n}_{ij}\right]_{\alpha}^{l}, \left[\overline{n}_{ij}\right]_{\alpha}^{u}\right)$. This $\overline{N}_{ij}$ be a normalized positive triangular fuzzy number.

Step. 6. Considering the every one criterion, we can construct the weighted normalized fuzzy decision matrix as $\overline{v}_{ij} = \overline{N}_{ij}.\overline{w}_{j}$ where $\overline{w}_{j}$ is the weight of the jth criterion.
Step. 7. Every one $\overline{v}_{ij}$ is a normalized fuzzy number and their ranges belong to [0, 1]. So we identify the PIS $\overline{A}^{+} = \left(\overline{v}_{1}^{+}, \overline{v}_{2}^{+}, ..., \overline{v}_{n}^{+}\right)$ and the NIS $\overline{A}^{-} = \left(\overline{v}_{1}^{-}, \overline{v}_{2}^{-}, ..., \overline{v}_{n}^{-}\right)$ where $\overline{v}_{j}^{+} = (1, 1, 1)$ and $\overline{v}_{j}^{-} = (0, 0, 0)$, $j = 1, 2, ..., n$ for every criteria.
Step. 8. Using the length definition, we calculate the length of every one alternatives from the PIS and NIS as $\overline{\delta}_{i}^{+} = \sum_{j=1}^{n} d\left(\overline{v}_{ij}, \overline{v}_{j}^{+}\right)$ and $\overline{\delta}_{j}^{-} = \sum_{j=1}^{n} d\left(\overline{v}_{ij}, \overline{v}_{j}^{-}\right)$ $i = 1, 2, ..., m$, respectively.
Step. 9. The relative closeness coefficients is $\overline{C}_{i} = \frac{\overline{\delta}_{i}^{-}}{\left(\overline{\delta}_{i}^{+} + \overline{\delta}_{i}^{-}\right)}$, $i = 1, 2, 3, ..., m$.

3 Research Methodology

Using the different steps to calculating the group of best alternatives is defined below:

The PIS A^{+}(benefits) and NIS A^{-}(costs) for each group member $r = 1, 2, \ldots, R$ as follows:

$$^{r}A^{+} = \left({}^{r}\overline{V}_{1}^{+}, {}^{r}\overline{V}_{2}^{+}, \cdots, {}^{r}\overline{V}_{m}^{+}\right) \text{ and } {}^{r}A^{-} = \left({}^{r}\overline{V}_{1}^{-}, {}^{r}\overline{V}_{2}^{-}, \cdots, {}^{r}V_{m}^{-}\right)$$

where ${}^{r}\overline{V}_{j}^{+} = \left(\max_{i} {}^{r}\overline{V}_{ij}, j \in J_1;\ \min_{i} {}^{r}\overline{V}_{ij}, j \in J_2\right)$.
and ${}^{r}\tilde{V}_{j}^{-} = \left(\min_{i} {}^{r}\tilde{V}_{ij}, j \in J_1;\ \max_{i} {}^{r}\tilde{V}_{ij}, j \in J_2\right)$.
where J_1 is criteria for benefit and J_2 is criteria for cost.
Evaluate the length of every one alternative for many members. The length of alternative A_i between the PIS and the NIS of the group members S_r, ${}^{r}\overline{D}_{i}^{+}$ and ${}^{r}\overline{D}_{i}^{-}$ is given with $i = 1, 2, \cdots, m$; $r = 1, 2, \cdots, R$ by:
${}^{r}\overline{D}_{i}^{+} = \sum_{j=1}^{n} D\left({}^{r}\overline{V}_{ij}, {}^{r}\overline{V}_{j}^{+}\right)$ and ${}^{r}\overline{D}_{i}^{-} = \sum_{j=1}^{n} D\left({}^{r}\overline{V}_{ij}, {}^{r}\overline{V}_{j}^{-}\right)$.
where the lengths $D\left({}^{r}\overline{V}_{ij}, {}^{r}\overline{V}_{j}^{+}\right)$ and $D\left({}^{r}\overline{V}_{ij}, {}^{r}\overline{V}_{j}^{-}\right)$ between two fuzzy numbers are calculated.
The relative closeness for every one alternative A_i of every one member r, $\overline{\Omega}^{r}(A_i)$ with respect to PIS as
$\overline{\Omega}^{r}(A_i) = \frac{{}^{r}\overline{D}_{i}^{-}}{{}^{r}\overline{D}_{i}^{+} + {}^{r}\overline{D}_{i}^{-}}$ with $i = 1, 2, \ldots, m;\ r = 1, 2, \ldots, R$
Now, we calculate the $\overline{\Omega}^{r}(A_i)$ for every one member r we may form the relative closeness matrix as given by:

$$Q = \begin{pmatrix} \overline{\Omega}^{1}(A_1) & \overline{\Omega}^{2}(A_1) & \cdots & \overline{\Omega}^{R}(A_1) \\ \overline{\Omega}^{1}(A_2) & \overline{\Omega}^{2}(A_2) & \cdots & \overline{\Omega}^{R}(A_2) \\ \vdots & \vdots & \ddots & \vdots \\ \overline{\Omega}^{1}(A_m) & \overline{\Omega}^{2}(A_m) & \cdots & \overline{\Omega}^{R}(A_m) \end{pmatrix}$$

The weighted RCM is given by:

$$Q\alpha = \begin{pmatrix} \alpha^{1}\overline{\Omega}^{1}(A_1) & \alpha^{2}\overline{\Omega}^{2}(A_1) & \cdots & \alpha^{R}\overline{\Omega}^{R}(A_1) \\ \alpha^{1}\overline{\Omega}^{1}(A_2) & \alpha^{2}\overline{\Omega}^{2}(A_2) & \cdots & \alpha^{R}\overline{\Omega}^{R}(A_2) \\ \vdots & \vdots & \ddots & \vdots \\ \alpha^{1}\overline{\Omega}^{1}(A_m) & \alpha^{2}\overline{\Omega}^{2}(A_m) & \cdots & \alpha^{R}\overline{\Omega}^{R}(A_m) \end{pmatrix}$$

To establish the groups, PIS and NIS

$$A_{G}^{+} = \left(V_{G1}^{+}, V_{G2}^{+}, \ldots, V_{GR}^{+}\right)$$

$$= \left(\max_i \alpha^1 \Omega^1(A_i), \max_i \alpha^2 \Omega^2(A_i), \ldots, \max_i \alpha^R \Omega^R(A_i) \right)$$

$$\text{and } A_G^- = \left(V_{G1}^-, V_{G2}^-, \ldots, V_{GR}^-\right)$$

$$= \left(\min_i \alpha^1 \Omega^1(A_i), \min_i \alpha^2 \Omega^2(A_i), \ldots, \min_i \alpha^R \Omega^R(A_i) \right)$$

Calculate to every one alternative A_i the lengths from the group positive and NISs A_{G}^+ and A_{G}^-, respectively, with $i = 1, 2, \cdots, m$ as follows:

$$d_{\mathrm{Gi}}^+ = \sqrt{\sum_{r=1}^{R} \left(\alpha^r \Omega^r(A_i) - V_{\mathrm{Gr}}^+\right)^2} \text{ and } d_{\mathrm{Gi}}^- = \sqrt{\sum_{r=1}^{R} \left(\alpha^r \Omega^r(A_i) - V_{\mathrm{Gr}}^-\right)^2}$$

Construct the group relative closeness Ω_{Gi} for every one alternative A_i with respect to GIS (group ideal solution) as:

$$\Omega_G(A_i) = \frac{d_{\mathrm{Gi}}^-}{d_{\mathrm{Gi}}^- + d_{\mathrm{Gi}}^+}$$

4 Computational Illustration

In this classification, we adduce one ciphering illustration to interpret the TOPSIS technique for DM problems with fuzzy data. Considering that, we have five alternatives Alt1, Alt2, Alt3, Alt4, Alt5 among which decision makers have to choose and evaluated by four experts or decision makers DM1, DM2, DM3, DM4 under fuzzy environment for behavior operational versus four benefit criteria Crt1, Crt2, Crt3, Crt4. The linguistic weights for performing the predominant of criteria are very little low (VLL), little low (LL), medium low (ML), medium little high (MLH), little high (LH), very little high (VLH), little excellent (LE) and excellent (E), with the following fuzzy numbers demarcated in Table 1.

Table 1 Linguistic terms

Linguistic terms	Fuzzy numbers
Very little low (VLL)	(0.0,0.0,0.12)
Little low (LL)	(0.0,0.12,0.24)
Medium little low (MLL)	(0.12,0.24,0.36)
Medium low (ML)	(0.24,0.36,0.48)
Medium little high (MLH)	(0.36,0.48,0.60)
Little high (LH)	(0.48,0.60,0.72)
Very little high (VLH)	(0.60,0.72,0.84)
Little excellent (LE)	(0.72,0.84,0.96)
Excellent (E)	(0.84,0.96,1.00)

Table 2 Performance of decision makers for alternatives and criteria

DM	Crt1	Crt2	Crt3	Crt4	Crt5	Crt6	Crt7
Alt1	MLL	VLL	LH	VG	E	VLH	ML
Alt2	G	LH	LE	LL	MLH	LP	LH
Alt3	LL	E	FLP	ML	VG	FLG	VLL
Alt4	LE	G	MLL	VLH	E	MG	ML
Alt5	MG	FLP	E	LH	LE	LH	LL
Alt6	LP	VG	MLH	LE	E	VLL	ML
Alt7	FLG	MG	MLL	FLP	G	VG	VLH
Alt8	LH	LE	G	VG	VLH	LL	LP
Alt9	VLL	MG	FLG	VG	MLH	E	LH

Based on the upper expansions, ourselves considering FTOPSIS for four decision matrices DM1, DM2, DM3 and DM4 with same appraises of weights with (0.250, 0.250, 0.250, 0.250). Evolved from this utility, we evaluated the DM, the NDM, the WNDM, fuzzy PIS, fuzzy NIS, the relative closeness coefficient for one after the other DM proportional to similar weights from Tables 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17 and 18. From Tables 3, 4, 5 and 6, we established the appraise using first DM with NDM, propositional to the weights, the fuzzy PIS and fuzzy NIS, relative closeness coefficient with ranking order. From Tables 7, 8, 9 and 10, we established the appraise using second DM with NDM, propositional to

Table 3 Decision matrix for DM1

DM1	Crt1	Crt2	Crt3	Crt4
Alt1	(0.00,0.00,0.12)	(0.24,0.36,0.48)	(0.84,0.96,1.00)	(0.48,0.6,0.72)
Alt2	(0.24,0.36,0.48)	(0.72,0.84,0.96)	(0.00,0.12,0.24)	(0.6,0.72,0.84)
Alt3	(0.60,0.72,0.84)	(0.24,0.36,0.48)	(0.12,0.24,0.36)	(0.84,0.96,1.0)
Alt4	(0.84,0.96,1.00)	(0.60,0.72,0.84)	(0.48,0.60,0.72)	(0.24,0.36,0.48)
Alt5	(0.48,0.60,0.72)	(0.72,0.84,0.96)	(0.60,0.72,0.84)	(0.12,0.24,0.36)

Table 4 Normalized decision matrix for DM1

DM1	Crt1	Crt2	Crt3	Crt4
Alt1	(0.00,0.00,0.12)	(0.25,0.375,0.50)	(0.84,0.96,1.00)	(0.48,0.6,0.72)
Alt2	(0.24,0.36,0.48)	(0.75,0.875,1.00)	(0.00,0.12,0.24)	(0.6,0.72,0.84)
Alt3	(0.60,0.72,0.84)	(0.25,0.375,0.50)	(0.12,0.24,0.36)	(0.84,0.96,1.0)
Alt4	(0.84,0.96,1.00)	(0.625,0.75,0.875)	(0.48,0.60,0.72)	(0.24,0.36,0.48)
Alt5	(0.48,0.60,0.72)	(0.75,0.875,1.00)	(0.60,0.72,0.84)	(0.12,0.24,0.36)

Table 5 Weighted normalized decision matrix for DM1

DM1	Crt1	Crt2	Crt3	Crt4
Alt1	(0.00,0.00,0.04)	(0.083,0.125,0.167)	(0.28,0.32,0.333)	(0.16,0.20,0.24)
Alt2	(0.08,0.12,0.16)	(0.25,0.291,0.333)	(0.00,0.04,0.08)	(0.20,0.24,0.28)
Alt3	(0.20,0.24,0.28)	(0.083,0.125,0.167)	(0.04,0.08,0.12)	(0.28,0.32,0.333)
Alt4	(0.28,0.32,0.333)	(0.208,0.25,0.291)	(0.16,0.20,0.24)	(0.08,0.12,0.16)
Alt5	(0.16,0.20,0.24)	(0.25,0.291,0.333)	(0.20,0.24,0.28)	(0.04,0.08,0.12)

Table 6 Length from PIS, NIS and closeness with ranking order for DM1

DM1	D.P.I.S	D.N.I.S	Ci	Ri
Alt1	0.576	0.391	0.404	5
Alt2	0.535	0.435	0.448	4
Alt3	0.47	0.498	0.515	2
Alt4	0.345	0.623	0.644	1
Alt5	0.415	0.554	0.572	2

Table 7 Decision Matrix for DM2

DM2	Crt1	Crt2	Crt3	Crt4
Alt1	(0.00,0.0,0.12)	(0.12,0.24,0.36)	(0.36,0.48,0.60)	(0.6,0.72,0.84)
Alt2	(0.0,0.12,0.24)	(0.24,0.36,0.48)	(0.48,0.60,0.72)	(0.72,0.84,0.96)
Alt3	(0.12,0.24,0.36)	(0.36,0.48,0.60)	(0.60,0.72,0.84)	(0.84,0.96,1.0)
Alt4	(0.24,0.36,0.48)	(0.48,0.60,0.72)	(0.72,0.84,0.96)	(0.00,0.0,0.12)
Alt5	(0.36,0.48,0.6)	(0.60,0.72,0.84)	(0.84,0.96,1.00)	(0.12,0.24,0.36)

Table 8 Normalized decision matrix for DM2

DM2	Crt1	Crt2	Crt3	Crt4
Alt1	(0.00,0.0,0.20)	(0.143,0.286,0.429)	(0.36,0.48,0.6)	(0.60,0.72,84)
Alt2	(0.0,0.20,0.40)	(0.286,0.429,0.571)	(0.48,0.6,0.72)	(0.72,0.84,0.96)
Alt3	(0.20,0.4,0.60)	(0.429,0.571,0.714)	(0.6,0.72,0.84)	(0.84,0.96,1.0)
Alt4	(0.40,0.60,0.80)	(0.571,0.714,0.857)	(0.72,0.84,0.96)	(0.00,0.00,0.12)
Alt5	(0.60,0.80,1.0)	(0.714,0.857,1.0)	(0.84,0.96,1.0)	(0.12,0.24,0.36)

Table 9 Weighted normalized decision matrix for DM2

DM2	Crt1	Crt2	Crt3	Crt4
Alt1	(0.00,0.0,0.067)	(0.048,0.095,0.143)	(0.12,0.16,0.2)	(0.20,0.24,0.28)
Alt2	(0.0,0.067,0.133)	(0.095,0.143,0.19)	(0.60,0.2,0.24)	(0.24,0.28,0.32)
Alt3	(0.067,0.133,0.20)	(0.143,0.19,0.238)	(0.2,0.24,0.28)	(0.28,0.32,0.333)
Alt4	(0.133,0.20,0.266)	(0.19,0.238,0.285)	(0.24,0.28,0.32)	(0.00,0.00,0.04)
Alt5	(0.20,0.266,0.333)	(0.238,0.285,0.333)	(0.28,0.32,0.333)	(0.04,0.08,0.12)

Table 10 Length from PIS, NIS and closeness with ranking order for DM2

DM2	D.P.I.S	D.N.I.S	Ci	Ri
Alt1	0.660	0.227	0.256	5
Alt2	0.488	0.4095	0.456	4
Alt3	0.300	0.588	0.662	2
Alt4	0.446	0.443	0.498	3
Alt5	0.231	0.657	0.740	1

Table 11 Decision matrix for DM3

DM3	Crt1	Crt2	Crt3	Crt4
Alt1	(0.6,0.72,0.84)	(0.36,0.48,0.60)	(0.72,0.84,0.96)	(0.36,0.48,0.6)
Alt2	(0.36,0.48,0.6)	(0.12,0.24,0.36)	(0.48,0.60,0.72)	(0.24,0.36,0.48)
Alt3	(0.72,0.84,0.96)	(0.84,0.96,1.00)	(0.60,0.72,0.84)	(0.6,0.72,0.84)
Alt4	(0.60,0.72,0.84)	(0.72,0.84,0.96)	(0.48,0.60,0.72)	(0.12,0.24,0.36)
Alt5	(0.36,0.48,0.6)	(0.84,0.96,1.00)	(0.00,0.12,0.24)	(0.48,0.6,0.72)

Table 12 Normalized decision matrix for DM3

DM3	Crt1	Crt2	Crt3	Crt4
Alt1	(0.625,0.75,0.875)	(0.36,0.48,0.60)	(0.75,0.875,1.00)	(0.429,0.571,0.714)
Alt2	(0.375,0.50,0.625)	(0.12,0.24,0.36)	(0.50,0.625,0.75)	(0.286,0.429,0.571)
Alt3	(0.75,0.875,1.00)	(0.84,0.96,1.00)	(0.625,0.75,0.875)	(0.714,0.857,1.00)
Alt4	(0.50,0.625,0.75)	(0.72,0.84,0.96)	(0.50,0.625,0.75)	(0.143,0.286,0.429)
Alt5	(0.375,0.50,0.625)	(0.84,0.96,1.00)	(0.00,0.125,0.25)	(0.571,0.714,0.857)

Table 13 Weighted normalized decision matrix for DM3

DM3	Crt1	Crt2	Crt3	Crt4
Alt1	(0.208,0.25,0.291)	(0.12,0.16,0.20)	(0.25,0.291,0.333)	(0.143,0.19,0.238)
Alt2	(0.125,0.167,0.208)	(0.04,0.08,0.12)	(0.167,0.208,0.25)	(0.095,0.143,0.19)
Alt3	(0.25,0.291,0.333)	(0.28,0.32,0.333)	(0.208,0.25,0.291)	(0.238,0.285,0.333)
Alt4	(0.167,0.208,0.25)	(0.24,0.28,0.32)	(0.167,0.208,0.25)	(0.048,0.095,0.143)
Alt5	(0.125,0.167,0.208)	(0.28,0.32,0.333)	(0.00,0.042,0.083)	(0.19,0.238,0.285)

Table 14 Length from PIS, NIS and closeness with ranking order for DM3

DM3	D.P.I.S	D.N.I.S	Ci	Ri
Alt1	0.288	0.508	0.638	2
Alt2	0.582	0.214	0.269	5
Alt3	0.042	0.755	0.948	1
Alt4	0.390	0.408	0.511	3
Alt5	0.422	0.374	0.470	4

Table 15 Decision matrix for DM4

DM4	Crt1	Crt2	Crt3	Crt4
Alt1	(0.00,0.00,0.12)	(0.00,0.12,0.24)	(0.24,0.36,0.48)	(0.72,0.84,0.96)
Alt2	(0.12,0.24,0.36)	(0.00,0.00,0.12)	(0.36,0.48,0.60)	(0.00,0.00,0.12)
Alt3	(0.00,0.12,0.24)	(0.12,0.24,0.36)	(0.00,0.00,0.12)	(0.48,0.60,0.72)
Alt4	(0.24,0.36,0.48)	(0.00,0.12,0.24)	(0.00,0.00,0.12)	(0.60,0.72,0.84)
Alt5	(0.36,0.48,0.60)	(0.84,0.96,1.00)	(0.72,0.84,0.96)	(0.00,0.00,0.12)

Table 16 Normalized decision matrix for DM4

DM4	Crt1	Crt2	Crt3	Crt4
Alt1	(0.00,0.00,0.20)	(0.00,0.12,0.24)	(0.25,0.375,0.50)	(0.75,0.875,1.0)
Alt2	(0.20,0.40,0.60)	(0.00,0.00,0.12)	(0.375,0.5,0.625)	(0.00,0.0,0.125)
Alt3	(0.00,0.20,0.40)	(0.12,0.24,0.36)	(0.00,0.00,0.125)	(0.5,0.625,0.75)
Alt4	(0.40,0.60,0.80)	(0.00,0.12,0.24)	(0.00,0.00,0.125)	(0.625,0.75,0.875)
Alt5	(0.60,0.80,1.00)	(0.84,0.96,1.00)	(0.75,0.875,1.00)	(0.0,0.00,0.125)

Table 17 Weighted normalized decision matrix for DM4

DM4	Crt1	Crt2	Crt3	Crt4
Alt1	(0.00,0.00,0.067)	(0.00,0.04,0.08)	(0.083,0.125,0.167)	(0.25,0.291,0.333)
Alt2	(0.067,0.133,0.20)	(0.00,0.00,0.04)	(0.125,0.167,0.208)	(0.00,0.00,0.042)
Alt3	(0.00,0.067,0.133)	(0.04,0.08,0.12)	(0.00,0.00,0.042)	(0.167,0.208,0.25)
Alt4	(0.133,0.20,0.266)	(0.00,0.04,0.08)	(0.00,0.00,0.042)	(0.208,0.25,0.291)
Alt5	(0.20,0.266,0.333)	(0.28,0.32,0.333)	(0.25,0.291,0.333)	(0.00,0.00,0.042)

Table 18 Length from PIS, NIS and closeness with ranking order for DM4

DM4	D.P.I.S	D.N.I.S	Ci	Ri
Alt1	0.684	0.424	0.382	3
Alt2	0.834	0.269	0.244	5
Alt3	0.792	0.319	0.287	4
Alt4	0.658	0.450	0.406	2
Alt5	0.278	0.822	0.747	1

the weights, the fuzzy PIS and fuzzy NIS, relative closeness coefficient with ranking order. From Tables 11, 12, 13 and 14, we established the appraise using third DM with NDM, propositional to the weights, the fuzzy PIS and fuzzy NIS, relative closeness coefficient with ranking order. From Tables 15, 16, 17 and 18, we established the appraise using fourth DM with NDM, propositional to the weights, the fuzzy PIS and fuzzy NIS, relative closeness coefficient with ranking order. From Tables 19, 20 and 21, we computed group relative closeness DM, the weighted group relative closeness DM, group fuzzy PIS and group fuzzy NIS. Hence, the ranking order of all RCM in the GDM with five alternatives is Alt 2 $<$ Alt 1 $<$ Alt 4 $<$ Alt 5 $<$ Alt 3 and best optimal is Alt 3.

Table 19 Group relative closeness matrix

Alternatives	Relative closeness decision matrix			
	DM1Ci	DM2Ci	DM3Ci	DM4Ci
Alt1	0.404	0.256	0.638	0.382
Alt2	0.448	0.456	0.269	0.244
Alt3	0.515	0.662	0.948	0.287
Alt4	0.644	0.498	0.511	0.406
Alt5	0.572	0.740	0.470	0.747

Table 20 Weighted group relative closeness matrix

Alternatives	Weighted relative closeness decision matrix			
	WDM1Ci	WDM2Ci	WDM3Ci	WDM4Ci
Alt1	0.101	0.064	0.1595	0.0955
Alt2	0.112	0.114	0.06725	0.061
Alt3	0.12875	0.1655	0.237	0.07175
Alt4	0.161	0.1245	0.12775	0.1015
Alt5	0.143	0.185	0.1175	0.18675

Table 21 Group FPIS, FNIS and ranking order

Alternatives	GFPIS	GFNIS	GRCC	Rank
Alt1	0.180482	0.09849	0.3530464	4
Alt2	0.228189	0.051196	0.1832446	5
Alt3	0.121018	0.200007	0.623027	1
Alt4	0.151206	0.112075	0.4256847	3
Alt5	0.120848	0.186395	0.6066696	2

5 Conclusion

The MCDM method having various applications in fuzzy TOPSIS DM problems. In the present study, the outcomes controvert those four different DM with weights of the projected techniques. The algorithm was planned and tabulated values are calculated using fuzzy TOPSIS software. We believe that the projected techniques manifest value but, as a obstruction, it is tough and impenetrable to estimate subjectively the fuzzy information in a realistic way while the results of the research are dependent on the experts opinions and linguistic variables. We demonstrated a MCDM technique, with DM, comprising of the value of a fuzzy number greater than or equal to another fuzzy number, a new inter-space measure of one after another fuzzy number from FPIS as well as FNIS. This method yields the optimal solution.

However, some surveillances are obtained from the given illustration; we are assertive the consequence for numerous illustrations would give us similar resolutions. We quite reflect a scads of illustrations should be nominated for test in future studies. Each and every topic allied to group intercommunications would be an interesting one for group DM and will be left for future study.

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