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A Modification of Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) through Fuzzy Similarity Method (a Numerical Example of the Personnel Selection)

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Abstract

Multiple Criteria Decision-Making (MCDM) is well known nowadays as a methodology in which a set of techniques are integrated to evaluate a set of alternatives with specified criteria for the purpose of selecting or ranking. The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is well-established methodology frequently considered in MCDM analysis. TOPSIS has a sound logic of human choice and is a scalar value simultaneously taking into account both the best and worst alternatives. Moreover, it has a simple computation process that could be easily programmed and finally it has the ability to rank alternatives on attributes to be visualized on a polyhedron, in at least two dimensions. Despite the advantages of this method, the process of ranking alternative according to related criteria may need more consideration. Typically, there are contributions in this article. First, a new similarity measure has been introduced followed by a modification applied to TOPSIS analyses. Second, the modified similarity technique was subsequently extended in the fuzzy context to cope with the uncertainty inherently existing in human judgments. A numerical example of the personnel selection was presented to demonstrate the possible application of the proposed method in human resource management. The outcome of applying fuzzy similarity method showed a significant distinction in ranking alternatives compered to TOPSIS method. Therefore, the modification is sound to be a proper solution.

Keywords: Multiple criteria decision-making, Fuzzy set theory, Modified similarity, Personnel selection, TOPSIS.

1 | Introduction

Multiple Criteria Decision-Making (MCDM) has been introduced and implemented as a procedure, by which a set of techniques are integrated to evaluate alternatives having a number of qualitative and/or quantitative criteria consisting of different measurement units with the aim of selecting or ranking [1]. It provides the users with the ability to comprehend the outcomes of integrated assessments, including tradeoffs among policy objectives, and using such results in a more systematic and defensible way to develop policy for purposeful recommendations [2]. The MCDM makes evaluation on a set of alternatives with respect to three objectives: 1) choosing the best alternative among a set of alternatives, 2) sorting the alternatives into relatively homogeneous groups or arranging them in a preferable order, and 3) ranking the alternatives in a descending or ascending order [3]. Since complexities in making a decision are increased nowadays, decisions are

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mainly made by groups of decision makers rather than individuals [4]. Therefore, Multiple Criteria Group Decision Making (MCGDM) problems have become common rather than MCDM, where a group of decision makers express their preferences, opinions and judgments about some alternatives in accordance with a set of criteria [5]. Nevertheless, personalization and predilection of opinions of decision makers could undeniably, have been involved in judgments [6]-[9]. Significant efforts in the field of developing and improving MCDM (and also MCGDM techniques) resulted in numerous approaches for effective addressing of multiple general criteria analysis decision problems [10]. The applications of these methods depend on the structure of decision problems [1]. Among all the different MCDM methods, the method Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) developed by Hwang and Yoon [11] is one of the most commonly used techniques, which was applied to many different areas such as production and operation management [12], human resource management [13], knowledge management [14], financial management [15], risk management [16], information technology [17], environmental management [18] and natural resources management [19]. Ranking alternatives in the TOPSIS method is based on the shortest distance from the Positive Ideal Solution (PIS) and the farthest from the Negative Ideal Solution (NIS). Some scholars such as [20], [21] and addressed four advantages of the TOPSIS method: 1) a sound logic that represents the rationale of human choice, 2) a scalar value simultaneously considering both the best and worst alternatives, 3) a simple computation process that could be easily programmed, and 4) ability of the performance measures of all alternatives on attributes to be visualized on a polyhedron, in at least two dimensions. Despite these advantages, the process of calculating the performance index for each alternative according to all criteria in the TOPSIS approach may need more consideration [22]. Mathematically, comparing two alternatives in the form of two vectors is better represented by the magnitude of the alternatives and the degree of conflict between each alternative and the ideal solution, instead of just calculating the relative distance between them [10]. To avoid this concern about TOPSIS, the most preferred alternative in the similarity method should have the highest degree of similarity to the PIS and the lowest degree of similarity to the NIS. The overall performance index of each alternative, according to all criteria, is determined based on the combination of these two degrees of similarity concepts using alternative gradient and magnitude. In other words, it should be better to measure the angle between alternatives and the ideal solution other than just calculating the distance between them. Deng [10] rectified this concern in his proposed similarity method, because the logic of calculating ideal solutions is the same but in the similarity method, this distance is calculating by the angle which is a better criterion. Some other authors used that as a technique to rank alternatives based on certain criteria. For example, similarity technique is used to risk analysis [23], [24], rank services for reliability estimation of Service-Oriented Architecture (SOA) [25] and also evaluating companies based on Corporate Governance (CG) measures [26]. In this article we show that the similarity method introduced by Deng [10] and used by the authors of this paper might also require additional consideration. In other words, the problem caused by relative similarity of the alternative to the NIS in Deng method is explained, and a proper modification for it is introduced. In summary, there are several MCDM techniques such as MABAC [27], COPRAS [28], RAFSI [29], VIKOR [30], [31] each of which, in addition to the advantages, are also having some disadvantages. The TOPSIS technique is no exception to this rule, and in addition to the advantages that make it one of the most common MCDM techniques, it has shortcomings that have been partially covered by the similariy technique but not completely eliminated.

The COPRAS quantitative multicriteria tool is applied with maximization and minimization of variables' values. It allows the user to compare and check calculated results easily. Going more deep into the comparative analysis of the COPRAS, it can be less stable in comparison with the TOPSIS tools on the case of variation of data; thus the COPRAS is used separately from other methods. In the COPRAS technique, we must have at least one indicator with a negative nature, but in the TOPSIS technique, the indicators can be positive or negative.

The main difference between VIKOR and TOPSIS appears in the aggregation approaches. The VIKOR method provides an aggregating function representing the distances from ideal solution. Addition to TOPSIS, VIKOR method provides a compromise solution with an advantage rate. The normalization

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procedures are different in each method. While the VIKOR method uses linear normalization, TOPSIS method uses vector normalization. In linear normalization, the normalized value does not depend to the unit of the criteria. In TOPSIS method, normalized value could be different for different evaluation unit of a particular criterion. The TOPSIS method uses n-dimensional Euclidean distance that by itself could represent some balance between total and individual satisfaction, but uses it in a different way than VIKOR, where weight v is introduced. Both methods provide a ranking list. The highest ranked alternative by VIKOR is the closest to the ideal solution. However, the highest ranked alternative by TOPSIS is the best in terms of the ranking index, which does not mean that it is always the closest to the ideal solution. In addition to ranking, the VIKOR method proposes a compromise solution with an advantage rate.

Three main advantages of the RAFSI method distinguish it from the other traditional MADM methods, which include: 1) RAFSI method enables DMs to solve complex problems, 2) use a new data normalization technique that converts an initial decision matrix into a unique criterion interval, and 3) resistance of the RAFSI method to rank reversal problems. Compared to the TOPSIS technique, the calculation rate of the TOPSIS technique is less.

Compared to the TOPSIS technique, MABAC has an easy computational process, organized procedure, and an innovative direction that determines the foundation of real-world decision-making problems. Therefore, the aim of the present article is to completely eliminate the shortcomings of the TOPSIS technique by modifying the similarity technique and also expanding it in a fuzzy atmosphere. The reason to select this techniquein pursuit of modification and optimization is the benefits listed for it and also the researchers' efforts to identify a solution to the issue that has been addressed and other researchers such as Deng [10] have also confirmed it. It is also suggested that investigators take the modification of other techniques into consideration if needed. The reseatch purpose is to develop a modified similarity method in a fuzzy environment to solve an important problem of the TOPSIS method based on the logic that the comparison of alternatives cannot be determined only by the distance from the PIS and NIS. There are two main contributions in this article. First, a new similarity measure has been introduced followed by a modification applied to TOPSIS analyses. Second, the modified similarity technique was subsequently extended in the fuzzy context to cope with the uncertainty inherently existing in human judgments. Rest of this paper is organized as follows. A detailed algorithmic procedure of the modified fuzzy similarity method is described in Section 2. Section 3 contains an illustrative example in human resource management to demonstrate the applicability of the proposed method. Finally, concluding remarks are given in Section 4.

2 | The Proposed Modified Fuzzy Similarity Method

The similarity method was presented in this section in order to use it while making decisions in fuzzy environments.

2.1 | The Similarity Method

In this part, the similarity method introduced by Deng [10] is presented in an algorithmic form. In addition, during the presentation of the method, a solution is provided for resolving a problem that exists in Deng's technique [10].

Step 1. Determining the decision matrix; the performance of each alternative (A_i) with respect to each criterion (C_j) is denoted as x_{ij}.

Step 2. Determining the weighting matrix; the relative importance of the criterion C_j with respect to the overall objective of the problem is represented as w_j.

Step 3. Normalizing the decision matrix through Euclidean normalization.

$$x'_{ij} = \frac{x_{ij}}{(\sum_{k=1}^{n} x_{ik}^2)^{1/2}}. \tag{2}$$

Step 4. Calculating the performance matrix by multiplying the normalized decision matrix X' by the weight vector W.

$$Y = \begin{bmatrix} w_1x'_{11} & w_2x'_{12} & \dots & w_mx'_{1m} \\ w_1x'_{21} & w_2x'_{22} & \dots & w_mx'_{2m} \\ \dots & \dots & w_ix'_{ij} & \dots \\ w_1x'_{n1} & w_2x'_{n2} & \dots & w_mx'_{nm} \end{bmatrix} = \begin{bmatrix} y_{11} & y_{12} & \dots & y_{1m} \\ y_{21} & y_{22} & \dots & y_{2m} \\ \dots & \dots & y_{ij} & \dots \\ y_{n1} & y_{n2} & \dots & y_{nm} \end{bmatrix}. \tag{3}$$

Step 5. Determining the PIS and the NIS; The positive (negative) ideal solution $I^+(I^-)$ consists of the best (worst) criteria values attainable from all the alternatives.

$$I_j^+ = \max y_{ij}^+ \, , I_j^- = \max y_{ij}^-. \tag{4}$$

Step 6. Calculating the conflict index between the alternatives and PIS and NIS.

As mentioned earlier, according to Deng [10], the logic of TOPSIS method in ranking the alternatives according to their distances from PIS and NIS could be problematic in some circumstances [10]. In this regard some researchers introduced better measures than just distance in order to compare the alternatives to PIS and NIS. Deng [10] introduced the concept of alternative gradient to represent the conflict of alternatives in multiple criteria analysis problems. Assume that A_i is a vector representing an alternative and that I_j^+ and I_j^- are two vectors of the positive and the NISs in a given multiple criteria analysis problem. These vectors can be considered in the m-dimensional real space. The angle between A_i and $I_j^+(I_j^-)$ in the m-dimensional real space, which is being shown by $\theta^+{}_i(\theta^-{}_i)$, is a good conflict measure between the vectors. The above vectors and the conflict degree between them are shown in *Fig.* . The situation of conflict occurs when $\theta_i \neq 0$, i.e., when the gradients of A_i and $I_j^+(I_j^-)$ are not coincident. Thus, the conflict index is equal to one when the corresponding gradient vectors lie in the same direction, and the conflict index is zero when $\theta_i = \pi/2$, which indicates that their gradient vectors have a perpendicular relationship between each other.

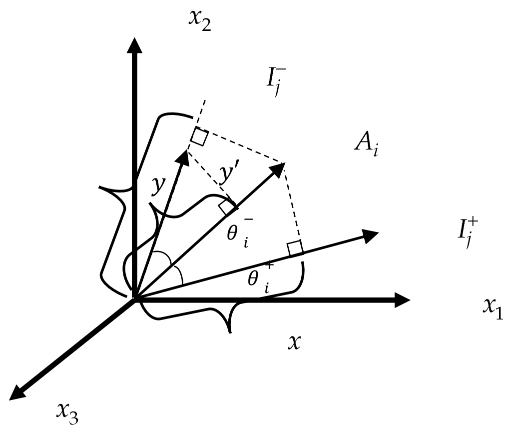

Fig. 1. The degree of conflict between alternatives and $I_j^+(I_j^-)$.

The degree of conflict between alternative A_i and $I_j^+(I_j^-)$ is determined by:

$$\cos\theta_i^+ = \frac{\sum_{j=1}^{m} y_{ij} \times I_j^+}{(\sum_{j=1}^{m} y_{ij}^2 \sum_{j=1}^{m}(I_j^+)^2)^{1/2}}, \quad i = 1,2,\dots,n,$$
$$\cos\theta_i^- = \frac{\sum_{j=1}^{m} y_{ij} \times I_j^-}{(\sum_{j=1}^{m} y_{ij}^2 \sum_{j=1}^{m}(I_j^-)^2)^{1/2}}, \quad i = 1,2,\dots,n. \tag{5}$$

Step 7. Calculating the degree of similarity of the alternatives to PIS and NIS.

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The similarity degree denoted as S_i^+, measures the relative similarity of the alternative A_i to I_j^+, and the degree of similarity denoted as S_i^- measures the relative similarity of the alternative A_i to I_j^-.

$$S_i^+ = \frac{x}{|I_j^+|} = \frac{\cos\theta_i^+ \, |A_i|}{|I_j^+|}, \quad i = 1,2, \dots, n. \tag{6}$$

The problem caused by S_i^- in Deng's method [10] is that, if we calculate S_i^- just like S_i^+, i.e., if we consider the equation $S_i^- = \frac{y}{|I^-|}$, a number is determined which is not between 0 and 1 for S_i^- and thus an issue is encountered with calculating the performance index in the next step. x is the projection of the alternative vector A_i on the PIS vector I_j^+. Since PIS has the highest value among alternatives, the A_i vector is equal or shorter than it. As a result, we will have a number between 0 and 1 for S_i^+. Similarly y is the projection of the alternative vector A_i on the NIS vector I_j^-. But in this case, as the NIS has the lowest value among alternatives, y is equal or longer than I_j^- and the problem is caused by Deng's method [10]. In order to fix the problem another vector is required and y' is the best choice. y' is the projection of the NIS vector (I_j^-) on the alternative vector (A_i), which is always lower than the alternative vector. Thus, *Eq. (7)* is proposed to overcome the problem related to Deng's method.

$$S_i^- = \frac{y'}{|A_i|} = \frac{\cos\theta_i^- \, |I_j^-|}{|A_i|}, \quad i = 1,2, \dots, n. \tag{7}$$

With this change in the calculation, a number between 0 and 1 for S_i^- and S_i^+ is obtained. This solves a significant problem that Deng [10], as well as some other scholars, have pointed out [10]-[25].

Step 8. Calculating the overall performance index for each alternative according to all criteria.

The overall performance index P_i can be calculated based on the concept of the similarity degree of alternative A_i to the ideal solutions.

$$P_i = \frac{S_i^+}{S_i^+ + S_i^-}, \qquad i = 1,2, \dots, n. \tag{8}$$

In the modified similarity method, which contrasts with the similarity method presented by Deng [10], S_i^- and P_i are always between 0 and 1. To the extent A_i becomes more similar to I_j^+, and less similar to I_j^-, the overall performance index P_i becomes near to 1.

Step 9. Ranking alternatives in the descending order based on the overall performance index value.

2.2 | Fuzzzy Context

MCDM often involves uncertainty, which can be tackled by employing the fuzzy sets theory [32]. Zadeh [33] proposed the "fuzzy sets theory" to model subjective decision-making processes. Therefore, the fuzzy versions of MCDM techniques are more suitable for subjective and qualitative assessments other than the classical MCDM techniques, which apply crisp values [34]-[36]. Thus, as an additional contribution, this article introduces the modified fuzzy similarity method to allow decision-makers to evaluate and rank alternatives systematically based on their specific criteria with different levels of importance (weights).

A fuzzy set $A = \{(x, \mu_A x)) \,|\, x \in X\}$ is a set of ordered pairs. Let the universe of discourse X be the subset of real number R, where $\mu_A x)$ is called the membership function, which assigns to each object x a grade of membership ranging between zero and one [37].

A positive triangular fuzzy number A , shown in *Fig. 2*, could be defined as $A = (l, m, u)$ where $l \le m \le u$ and l>0.

According to [38] the membership function $\mu_A(x)$ is defined as:

$$\mu_{\tilde{A}}(x)=\begin{cases} 0, & \text{if} \quad x < l, \\ \frac{x-l}{m-l}, & \text{if} \quad l < x < m, \\ \frac{u-x}{u-m}, & \text{if} \quad m < x < u, \\ 0, & \quad u < x. \end{cases} \quad (1)$$

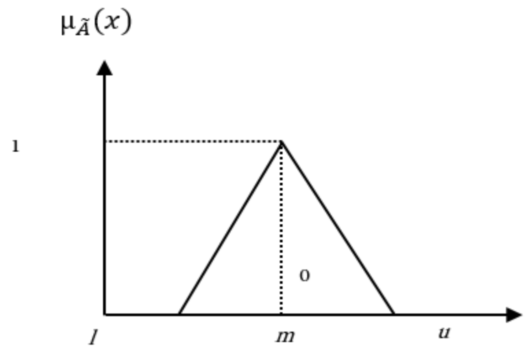

Fig. 2. Membership function of the triangular fuzzy number $\widetilde{A} = (l, m, u)$.

Zadeh [39], [40] offered linguistic variables as a practical means of describing complicated or hard-to-define situations. A linguistic variable is a variable, in which the values are expressed in linguistic terms, which are not numbers but words or sentences in a natural or artificial language.

2.3 | The Modified Fuzzy Similarity Method

Here the similarity method introduced by Deng [10] and its modified version are presented in detail. In this part, a modified fuzzy similarity method was introduced in an algorithmic form.

Step 1. Determining the fuzzy decision matrix.

The decision matrix in the fuzzy environment X is an n×m matrix in which a number of alternatives $A_i(I = 1,2, \ldots, n)$ are evaluated against a set of criteria $C_j(j = 1,2, \ldots, m)$, however, the data are fuzzy triangular numbers. The performance of each alternative A_i with respect to each criterion C_j, is denoted as x_{ij} so that:

$$x_{ij} = \left(l_{ij}, m_{ij}, u_{ij}\right). \quad (9)$$

Step 2. Determining the fuzzy weighting matrix.

The fuzzy weighting vector $\widetilde{W}$ represents the relative importance of each criterion.

$$\widetilde{w}_j = \left(w_j^{l}, w_j^{m}, w_j^{u}\right). \quad (10)$$

Step 3. Normalizing the fuzzy decision matrix through linear normalization:

A normalized decision matrix X' can be determined as:

$$X' = \begin{bmatrix} x'_{11} & x'_{12} & \cdots & x'_{1m} \\ x'_{21} & x'_{22} & \cdots & x'_{2m} \\ \cdots & \cdots & x'_{ij} & \cdots \\ x'_{n1} & x'_{n2} & \cdots & x'_{nm} \end{bmatrix}.$$

In which

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$$\begin{cases} \text{if } c_j \text{ is a benefit criterion then: } x'_{ij} = \left(\frac{l_{ij}}{\max_{i=1,\dots,n}(u_{ij})}, \frac{m_{ij}}{\max_{i=1,\dots,n}(u_{ij})}, \frac{u_{ij}}{\max_{i=1,\dots,n}(u_{ij})}\right), \\ \text{if } c_j \text{ is a cost criterion then: } \quad x'_{ij} = \left(\frac{\min_{i=1,\dots,n}(l_{ij})}{u_{ij}}, \frac{\min_{i=1,\dots,n}(l_{ij})}{m_{ij}}, \frac{\min_{i=1,\dots,n}(l_{ij})}{l_{ij}}\right). \end{cases} \tag{11}$$

Step 4. Calculating the fuzzy performance matrix.

The fuzzy performance matrix Y is calculated as below:

$$y_{ij} = x'_{ij} \otimes \widetilde{w}_j.$$

In which

$$y_{ij} = \left(y_{ij}{}^{l}, y_{ij}{}^{m}, y_{ij}{}^{u}\right) = \left(x'^{\,l}_{ij} \times w_j{}^{l}, x'^{\,m}_{ij} \times w_j{}^{m}, x'^{\,u}_{ij} \times w_j{}^{u}\right). \tag{12}$$

Step 5. Determining the fuzzy PIS and the fuzzy NIS:

$$\begin{aligned} I_j^{+} &= \left(I_j^{+l}, I_j^{+m}, I_j^{+u}\right) = \left(\max y_{ij}{}^{l}, \max y_{ij}{}^{m}, \max y_{ij}{}^{u}\right), \\ I_j^{-} &= \left(I_j^{-l}, I_j^{-m}, I_j^{-u}\right) = \left(\min y_{ij}{}^{l}, \min y_{ij}{}^{m}, \min y_{ij}{}^{u}\right). \end{aligned} \tag{13}$$

Step 6. Calculating the conflict index between the alternatives and PIS and NIS:

In this step, the fuzzy performance matrix Y, which consists of fuzzy triangular numbers is divided into three lower Y^l, middle Y^m and upper Y^u matrixes. Then *Eq. (5)* is calculated for each matrix separately. For example, the conflict index between the alternatives and PIS and NIS for the lower matrix Y^l is calculated as below:

$$\begin{aligned} \cos\theta_i^{+l} &= \frac{\sum_{j=1}^{m} y_{ij}{}^{l} \times I_j^{+l}}{\left(\sum_{j=1}^{m} y_{ij}^{2l} \sum_{j=1}^{m} (I_j^{+})^{2l}\right)^{1/2}}, \quad i = 1,2,\dots,n, \\ \cos\theta_i^{-l} &= \frac{\sum_{j=1}^{m} y_{ij}{}^{l} \times I_j^{-l}}{\left(\sum_{j=1}^{m} y_{ij}^{2l} \sum_{j=1}^{m} (I_j^{-})^{2l}\right)^{1/2}}, \quad i = 1,2,\dots,n. \end{aligned} \tag{14}$$

Step 7. Calculating the degree of similarity of the alternatives between each alternative and PIS and NIS.

Eq. (6) and *Eq. (7)* are calculated for lower Y^l, middle Y^m and upper Y^u matrices separately. For example, with respect to the lower matrix:

$$\begin{aligned} S_i^{+l} &= \frac{\cos\theta_i^{+} \left|A_i{}^{l}\right|}{\left|I_j^{+l}\right|}, \quad i = 1,2,\dots,n, \\ S_i^{-l} &= \frac{\cos\theta_i^{-l} \left|I_j^{-l}\right|}{\left|A_i{}^{l}\right|}, \quad i = 1,2,\dots,n. \end{aligned} \tag{15}$$

The modification applied to the similarity method in relation to calculating S_i^{-}, is repeated here for calculating *Eq. (15)*.

Step 8. Calculating the degree of similarity of the alternatives between each alternative and PIS and NIS.

In the fuzzy environment, p_i is a triangular fuzzy number, which is calculated for each alternative as below:

$$p_i = (p_i^{l}, p_i^{m}, p_i^{u}) = \left(\frac{s_i^{+l}}{s_i^{+u}+s_i^{-u}}, \frac{s_i^{+m}}{s_i^{+m}+s_i^{-m}}, \frac{s_i^{+u}}{s_i^{+l}+s_i^{-l}}\right),\ i = 1,2,\dots,n \quad (16)$$

Step 9. Ranking alternatives in the descending order based on the fuzzy overall performance index value.

In this step we have n fuzzy triangular numbers (p_i , $i = 1, 2,\dots,n$), which should be ranked. Thus, we compute the degree of possibility for each p_k fuzzy number to be higher than (n-1) other $\tilde{p}_i$ fuzzy numbers. According to [37] this can be defined as below:

$$V(P_k \geq P_1, P_2, \dots, P_n) = V(P_k \geq P_1) \text{ and } V(P_k \geq P_2) \ \dots\ V(\widetilde{P_k \geq P_n}) = \min V(P_k \geq P_i),\ i = 1,2,\dots,n. \quad (17)$$

In which the degree of possibility of $P_k \geq P_i$ is defined as:

$$V(P_k \geq P_i) = hgt(P_k \cap P_i) = \begin{Bmatrix} 1, & \text{if } m_k \geq m_i, \\ 0, & \text{if } l_i \geq u_k, \\ \dfrac{l_i - u_k}{m_k - u_k) - m_i - l_i)}, & \text{otherwise} \end{Bmatrix}. \quad (18)$$

The result of computing *Eq. (17)* and *Eq. (18)* for each alternative are crisp numbers that could be the basis of ranking alternatives.

3 | Numerical Example

In this section, a case study has been demonstrated to illustrate the applicability and validity of the proposed modified fuzzy similarity method. Suppose that a bank intends to choose an officer for the international marketing department from seven candidates named A_1, A_2, A_3, A_4, A_5, A_6, and A_7. A group of decision-makers consisting of three experts (E_1: manager of international marketing department, E_2: an executive from human resource department and E_3: an executive from the credit department) has been formed to assess the candidates, some of whom were already employed by the bank in other departments. The committee intends to rank the candidates based on six assessment criteria. These criteria are general criteria which have used in many research; some of them are shown in *Table 1*.

Table 1. Criteria for employee selection.

Symbol	Criteria	References
C1	Experience in marketing	Nong and Ha [41], Karabašević et al. [42], Polychroniou and Giannikos [43]
C2	Personality characteristics	Nong and Ha [41], Polychroniou and Giannikos [43]
C3	Knowledge of foreign languages	Widianta et al. [44], Nong and Ha [41], Polychroniou and Giannikos [43]
C4	Interpersonal communication skills	Widianta et al. [44], Abdullah et al. [45], Polychroniou and Giannikos [43]
C5	Educational background	Nong and Ha [41], Polychroniou and Giannikos [43], Karabašević et al. [42]
C6	Annual salary request	Polychroniou and Giannikos [43]

It is clear that the five first criteria are benefits (the higher, the better), and the sixth criterion is cost (the lower, the better). So this example, in contrast to many other numerical examples presented in this field (see for example [46]-[51]), includes both two types of criteria (benefit and cost).

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The procedure of the modified fuzzy similarity method for ranking candidates (alternatives) based on the six assessment criteria is described as below:

Step 1. Determining the fuzzy decision matrix.

The candidates' assessment by experts based on the six criteria is expressed through linguistic variables. According to [52], the triangular fuzzy conversion scale was used to convert linguistic values into fuzzy scales and is shown in *Table 2*.

Table 2. Linguistic variables and their respected fuzzy numbers.

Linguistic Variables		Corresponding Triangular Fuzzy Number
Evaluating the candidates based on assessment criteria	Importance of assessment criteria	
Very Poor (VP)	Very Low (VL)	(1,1,3)
Poor (P)	Low (L)	(1,3,5)
Fair (F)	Moderate (M)	(3,5,7)
Good (G)	High (H)	(5,7,9)
Very Good (VG)	Very High (VH)	(7,9,9)

The geometric mean of the three experts' judgments for each candidate based on the assessment criteria is calculated through the geometric mean technique in the fuzzy area [53] and is shown in *Table 3*. This table shows the fuzzy decision matrix.

$$X = (x^{1)} \otimes x^{2)} \otimes \ldots \otimes x^{n)})^{1/n}. \tag{19}$$

Table 3. The fuzzy decision matrix.

	C_1	C_2	C_3	C_4	C_5	C_6
A_1	(1.44,2.47,4.72)	(2.08,4.22,6.26)	(1.00,2.08,4.22)	(2.08,4.22,6.26)	(1.71,3.98,6.08)	(1.44,3.56,5.59)
A_2	(2.47,4.72,6.80)	(3.00,5.00,7.00)	(2.08,4.22,6.26)	(3.00,5.00,7.00)	(3.56,5.59,7.61)	(3.56,5.59,7.61)
A_3	(3.56,5.59,7.61)	(3.00,5.00,7.00)	(3.00,5.00,7.00)	(3.56,5.59,7.61)	(3.56,5.59,7.61)	(4.22,6.26,8.28)
A_4	(1.71,3.98,6.08)	(4.71,6.80,8.28)	(7.00,7.61,9.00)	(3.27,5.74,7.40)	(4.22,6.26,8.28)	(5.59,7.00,9.00)
A_5	(1.44,1.71,3.98)	(3.00,5.00,7.00)	(2.92,3.66,6.24)	(2.08,2.92,5.28)	(4.72,6.26,8.28)	(3.00,5.00,7.00)
A_6	(2.47,3.27,5.74)	(2.08,2.92,5.28)	(2.47,3.27,5.74)	(3.00,5.00,7.00)	(2.47,4.72,6.80)	(4.22,6.26,8.28)
A_7	(1.00,2.08,4.22)	(3.98,6.08,7.61)	(3.27,5.74,7.40)	(3.00,5.00,7.00)	(2.08,4.22,6.26)	(3.00,5.00,7.00)

Step 2. Determining the fuzzy weighting matrix.

The three experts assigned subjective weights to the six criteria according to their perceived importance. These weights were expressed based on linguistic variables, whose values are shown in *Table 2*. The weights assigned by the three experts (E_1, E_2, and E_3) are given in *Table 4*. The fuzzy weighting vector for each criterion is calculated using *Eq. (19)*, and normalized using *Eq. (11)* which are shown in *Table 4*.

Table 4. The fuzzy weighting matrix.

	C_1	C_2	C_3	C_4	C_5	C_6
A_1	(0.19,0.32,0.62)	(0.25,0.51,0.76)	(0.11,0.23,0.47)	(0.27,0.55,0.82)	(0.21,0.48,0.73)	(0.26,0.41,1.00)
A_2	(0.32,0.62,0.89)	(0.36,0.60,0.85)	(0.23,0.47,0.70)	(0.39,0.66,0.92)	(0.43,0.68,0.92)	(0.19,0.26,0.41)
A_3	(0.47,0.73,1.00)	(0.36,0.60,0.85)	(0.33,0.56,0.78)	(0.47,0.73,1.00)	(0.43,0.68,0.92)	(0.17,0.23,0.34)
A_4	(0.22,0.52,0.80)	(0.57,0.82,1.00)	(0.78,0.85,1.00)	(0.43,0.75,0.97)	(0.51,0.76,1.00)	(0.16,0.21,0.26)
A_5	(0.19,0.22,0.52)	(0.36,0.60,0.85)	(0.32,0.41,0.69)	(0.27,0.38,0.69)	(0.57,0.76,1.00)	(0.21,0.29,0.48)
A_6	(0.32,0.43,0.75)	(0.25,0.35,0.64)	(0.27,0.36,0.64)	(0.39,0.66,0.92)	(0.30,0.57,0.82)	(0.17,0.23,0.34)
A_7	(0.13,0.27,0.55)	(0.48,0.73,0.92)	(0.36,0.64,0.82)	(0.39,0.66,0.92)	(0.25,0.51,0.76)	(0.21,0.29,0.48)

Table 5. The normalized fuzzy decision matrix.

	E_1	E_2	E_3	$\widetilde{w}_j$
C_1	VH	H	H	(0.62,0.85,1.00)
C_2	H	VH	M	(0.52,0.76,0.92)
C_3	VH	M	M	(0.44,0.68,0.85)
C_4	H	VH	M	(0.52,0.76,0.92)
C_5	M	H	M	(0.40,0.62,0.85)
C_6	VH	VH	M	(0.59,0.82,0.92)

Step 3. Normalizing the fuzzy decision matrix through linear normalization.

The normalized fuzzy decision matrix $\widetilde{X'}$, as shown in *Table 5*, is calculated based on *Eq. (11)*.

Step 4. Calculating the fuzzy performance matrix.

The fuzzy performance matrix Y, which is calculated from *Eq. (12)*, is shown in *Table 6*.

Table 6. The fuzzy performance matrix.

	C_1	C_2	C_3	C_4	C_5	C_6
A_1	(0.12,0.27,0.62)	(0.13,0.39,0.70)	(0.05,0.16,0.40)	(0.14,0.42,0.76)	(0.08,0.30,0.62)	(0.15,0.33,0.92)
A_2	(0.20,0.52,0.89)	(0.19,0.46,0.78)	(0.10,0.32,0.59)	(0.21,0.50,0.85)	(0.17,0.42,0.78)	(0.11,0.21,0.37)
A_3	(0.29,0.62,1.00)	(0.19,0.46,0.78)	(0.15,0.38,0.66)	(0.24,0.56,0.92)	(0.17,0.42,0.78)	(0.10,0.19,0.31)
A_4	(0.14,0.44,0.80)	(0.30,0.62,0.92)	(0.34,0.57,0.85)	(0.23,0.57,0.89)	(0.20,0.47,0.85)	(0.09,0.17,0.24)
A_5	(0.12,0.19,0.52)	(0.19,0.46,0.78)	(0.14,0.27,0.59)	(0.14,0.29,0.64)	(0.23,0.47,0.85)	(0.12,0.24,0.44)
A_6	(0.20,0.36,0.75)	(0.13,0.27,0.59)	(0.12,0.25,0.54)	(0.21,0.50,0.85)	(0.12,0.35,0.70)	(0.10,0.19,0.31)
A_7	(0.08,0.23,0.55)	(0.25,0.56,0.85)	(0.16,0.43,0.70)	(0.21,0.50,0.85)	(0.10,0.32,0.64)	(0.12,0.24,0.44)

Step 5. Determining the fuzzy PIS and the fuzzy NIS.

The fuzzy PIS and the fuzzy NIS for each criterion are calculated based on *Eq. (13)* and are shown in *Table 7*.

Table 7. The fuzzy performance matrix.

	C_1	C_2	C_3	C_4	C_5	C_6
PIS	(0.29,0.62,1.00)	(0.30,0.62,0.92)	(0.34,0.57,0.85)	(0.24,0.57,0.92)	(0.23,0.47,0.85)	(0.15,0.33,0.92)
NIS	(0.08,0.19,0.52)	(0.13,0.27,0.59)	(0.05,0.16,0.40)	(0.14,0.29,0.64)	(0.08,0.30,0.62)	(0.09,0.17,0.24)

Step 6. Calculating the conflict index between the alternatives and PIS and NIS.

The conflict index between the alternatives and PIS and NIS, shown in *Table 8*, is calculated for lower, middle, and upper-performance matrixes separately based on *Eq. (14)*.

Table 8. The conflict index between the alternatives and the PIS and the NIS.

	Lower Performance Matrix		Middle Performance Matrix		Upper Performance Matrix	
	$\cos\theta^{+l}$	$\cos\theta^{-l}$	$\cos\theta^{+m}$	$\cos\theta^{-m}$	$\cos\theta^{+U}$	$\cos\theta^{-U}$
A_1	0.88	0.98	0.95	0.98	0.98	0.92
A_2	0.95	0.97	0.99	0.97	0.97	0.99
A_3	0.95	0.93	0.98	0.95	0.96	0.99
A_4	0.97	0.88	0.99	0.96	0.95	0.99
A_5	0.95	0.93	0.94	0.98	0.97	0.98
A_6	0.95	0.95	0.96	0.97	0.97	0.99
A_7	0.93	0.96	0.96	0.96	0.97	0.98

Step 7. Calculating the degree of similarity of the alternatives between each alternative and PIS and NIS.

The similarity degree is calculated for lower, middle, and upper-performance matrixes separately based on *Eq. (15)* and are shown in *Table 9*.

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Table 9. The degree of similarity of the alternatives to PIS and NIS.

	Lower Performance Matrix		Middle Performance Matrix		Upper Performance Matrix	
	S^+	S^-	S^+	S^-	S^+	S^-
A_1	0.39	0.85	0.56	0.72	0.74	0.70
A_2	0.60	0.59	0.76	0.55	0.78	0.71
A_3	0.72	0.47	0.83	0.49	0.82	0.66
A_4	0.85	0.38	0.91	0.45	0.83	0.65
A_5	0.57	0.59	0.58	0.68	0.69	0.79
A_6	0.55	0.63	0.60	0.69	0.69	0.80
A_7	0.58	0.59	0.71	0.57	0.73	0.74

Step 8. Calculating the fuzzy overall performance index for each alternative according to all criteria in the fuzzy environment.

The fuzzy overall performance index is calculated through *Eq. (16)* and is shown in *Table 10*.

Table 10. The fuzzy overall performance index values.

	P_i
A_1	(0.27,0.44,0.60)
A_2	(0.40,0.58,0.66)
A_3	(0.48,0.63,0.69)
A_4	(0.58,0.67,0.67)
A_5	(0.39,0.46,0.60)
A_6	(0.37,0.46,0.58)
A_7	(0.39,0.56,0.63)

Step 9. Ranking alternatives in the descending order based on the fuzzy overall performance index value.

The fuzzy overall performance index values are ranked in descending order through *Eqs. (17)* and *(18)*. The minimum degree of possibility for each overall performance index is higher than the other five overall performance indices, and the ranking order of the six candidates is shown in *Table 11*. Results show that with regard to the experts' judgments, the fourth candidate is the best candidate for the international marketing department officer position.

Table 11. The overall performance indices and ranks.

Candidate	Rank based on Fuzzy Similarity	Rank based on Fuzzy TOPSIS	Rank based on Fuzzy GTMA	Rank based on Fuzzy EDAS
A_1	6	4	6	6
A_2	3	3	3	1
A_3	2	2	1	2
A_4	1	1	2	3
A_5	5	5	5	5
A_6	7	6	4	7
A_7	4	7	7	4

The decision matrix options were then compared with other ranking techniques such as Fuzzy TOPSIS, Fuzzy GTMA and Fuzzy EDAS. The results of this ranking are shown in *Table 12*.

Table 12. The results of the various options ranking using different techniques.

Candidate	Rank based on Fuzzy Similarity	Rank based on Fuzzy TOPSIS	Rank based on Fuzzy GTMA	Rank based on Fuzzy EDAS
A_1	6	4	6	6
A_2	3	3	3	1
A_3	2	2	1	2
A_4	1	1	2	3
A_5	5	5	5	5
A_6	7	6	4	7
A_7	4	7	7	4

As shown in *Fig. 3*, option A_5 had the same result in all four techniques. Options A_2, A_1, and A_3 had similar results in three techniques. Option A_4 has the same result in the two techniques fuzzy similarity and fuzzy TOPSIS.

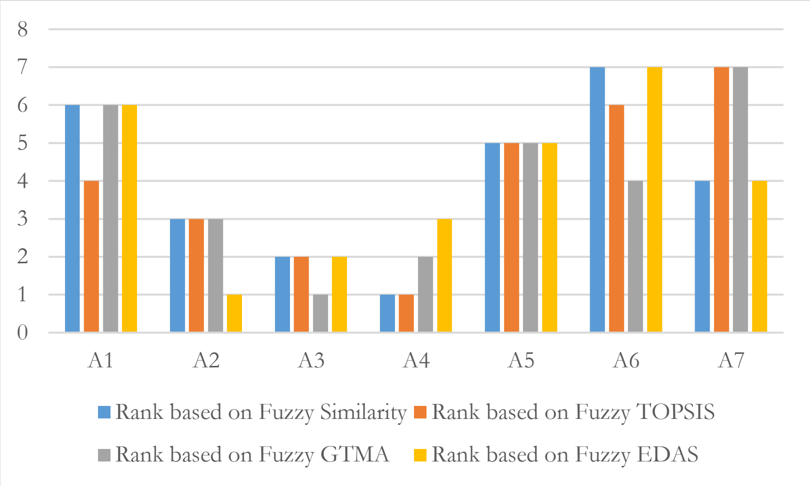

Fig. 3. Ranking results comparison.

4 | Conclusions

This paper presented a new MCDM method in a fuzzy environment. We showed that this technique could solve an important problem of the TOPSIS method based on the logic that the comparison of alternatives cannot be determined only by the distance from the PIS and NIS. Like TOPSIS, the similarity method compares the alternatives to PIS and NIS, but the comparison in similarity method is based on a broader concept. In the similarity method, the overall performance index of each alternative according to all criteria is determined based on the combination of the similarity degree to PIS and NIS using alternative gradient and magnitude. The proposed modified fuzzy similarity method is an extension of the method, which was introduced by Deng [10]. In fact, the proposed method has two significant contributions. First, it provides a solution for resolving the problem that exists in calculation of the similarity degree of the alternatives to NIS in Deng's technique [10]. The proposed method was applied in order to rank counties in terms of Human Development Index (HDI) and ranking countries based on CG measures by the authors but in the crisp format [54]. Second, the modified similarity method is extended to the fuzzy environment. The fuzzy similarity technique is also used to rank SOA [25] and risk analysis [23], but these two works have not considered the proposed modification of NIS shown in step 7. In this paper the modified similarity method was applied step by step. The results of this research show that simillarity is a good alternative to the TOPSIS method, but the innovation and distinguishing feature of the present paper is that it has expanded in fuzzy space and, secondly, has eliminated one of the shortcomings of the similiarity method mentioned earlier. Furthermore, a group of researches have already addressed the shortcomings of the TOPSIS method. Research using intuitionistic fuzzy numbers which is an extension of the soft set theory [55], [56] or by hesitant fuzzy set environment [57] or suggestion new techniques such as Interval-Valued Hesitant Pythagorean Fuzzy Sets (IVHPFSs) have attempted to solve this problem [58], are examples of this research. The present study in conventional fuzzy space has tried to address the shortcomings of similiarity, which is itself an alternative to TOPSIS.In order to demonstrate the feasibility and applicability of the proposed method, a numerical example was presented. The example was chosen from human resource management subjects (employee selection) to enlist the uncertainty that exists in this area. Since human judgments are very complex due to their subjective and intangible nature, this example helped in exhibiting a suitable application of this method. In addition, in the presented numerical example, in contrast to many other numerical examples in the field of employee selection, both the benefit and the cost criteria were used. In the human resource management field, most decisions are taken subjectively according to the non-quantative nature of this field. MCDM techniques in general and Modified Similarity teqnique in

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particular surely could help decision makers select accurately by quantifing the criteria. Also, the fuzzy solution, could help all other human management decisions such as performance appraisal or in assessment centers. The proposed method could be applied for other ranking purposes in many other fields such as risk analysis, corporate performance comparison, ranking and selecting strategies, and supplier selection purposes. It is recommended to compare the results of ranking alternatives through the modified similarity or modified fuzzy similarity method with other MCDM methods like TOPSIS, Superiority and Inferiority Ranking, Preference Ranking Organization Method for Enrichment Evaluations especially in the case of more alternatives. For future validation of the proposed fuzzy method, exploring more cases and conducting more empirical studies could prove to be useful. This study had also some limitations. First of all, we use a numerical example to show the applicability of the method. May be the actual and more data make the work more complex. Therefore, it is suggested that researchers apply the method for more related data. Second, we focus on the limitations of TOPSIS in general and Similarity method in patricular. Modifying these two methods can improve them but overally it is possible to find more accurate methods in the MCDM word. Thus, it is suggested that future research focus on comparing modified fuzzy similarity method and other MCDM techniques.

Conflict of Interest

The authors declare that they have no conflict of interest.

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