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The Application of Fuzzy TOPSIS Approach to Personnel Selection for Padir Company, Iran

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Abstract

Due to the increasing competition of globalization and fast technological improvements, world markets demand companies to have quality and professional human resources. This can only be achieved by employing potentially adequate personnel. This research adopts the fuzzy TOPSIS as the analytical tool that determines the weights of each criterion. Fuzzy theory provides a proper tool to encounter with uncertainties and complex environment. The purpose of this paper is to use the fuzzy TOPSIS method based on fuzzy sets in solving personnel selection problem. The result obtained by Fuzzy TOPSIS show that the second person (P_2) is the best person that should be employed.

Keywords: Personnel selection, Decision making, Fuzzy set and TOPSIS

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1. Introduction

In the global market, modern organizations face high levels of competition. In the wake of increasingly competitive world market the future survival of most companies, depends mostly on the dedication of their personnel to companies. Employee or personnel performances such as capability, knowledge, skill, and other abilities play an important role in the success of an organization. The main goal of organizations is to seek more powerful ways of ranking of a set employee or personnel who have been evaluated in terms of different competencies. Great deal of attention in literature was given for the selection of eligible and adequate person among alternative rivals and extensively conducted review can be found in Robertson and Smith (2001). The objective of a selection process depends mainly on assessing the differences among candidates and predicting the future performance. Latter is a challenging task since larger samples are required and other temporal changes may affect employees. Personality factors are generally described as emotional stability, extraversion, openness, agreeableness and conscientiousness Salgado (1997). Jessop (2004) determined seven criteria from overview of job description: written communication, oral communication, planning, organizing ability, team player, decisiveness, and working independently. One of the techniques concerning the selection of personnel to fill new positions is to have interviews with related personnel. Robertson and Smith (2001) and Cortina et al. (2000) present notable ability and availability of interviews to predict the performance of the personnel in the job. The usages of different methods in some European countries are given in Dany and Torchy (1994). The rest of the paper is organized as follows: The following section presents a concise treatment of the basic concepts of fuzzy set theory. Section 3 presents the methodology, fuzzy TOPSIS. The application of the proposed framework to personnel selection is addressed in Section 4. Finally, conclusions are provided in Section 5.

2. Fuzzy sets and Fuzzy Numbers

Fuzzy set theory, which was introduced by Zadeh (1965) to deal with problems in which a source of vagueness is involved, has been utilized for incorporating imprecise data into the decision framework. A fuzzy set $\tilde{A}$ can be defined mathematically by a membership function $\mu_{\tilde{A}}(X)$, which assigns each element *x* in the universe of discourse *X* a real number in the interval [0,1]. A triangular fuzzy number $\tilde{A}$ can be defined by a triplet (*a*, *b*, *c*) as illustrated in Fig 1.

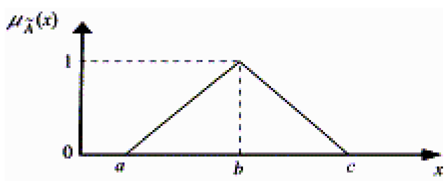

Fig 1 . A triangular fuzzy number $\tilde{A}$

The membership function $\mu_{\tilde{A}}(X)$ is defined as

$$\mu_{\tilde{A}}(x) = \begin{cases} \frac{x-a}{b-a} & a \leq x \leq b \\ \frac{x-c}{b-c} & b \leq x \leq c \\ 0 & oterwise \end{cases} \tag{1}$$

Basic arithmetic operations on triangular fuzzy numbers $A_1 = (a_1,b_1,c_1)$, where $a_1 \leq b_1 \leq c_1$, and $A_2 = (a_2,b_2,c_2)$, where $a_2 \leq b_2 \leq c_2$, can be shown as follows:

$$\text{Addition:} \quad A_1 \oplus A_2 = (a_1 + a_2, b_1 + b_2, c_1 + c_2) \tag{2}$$

$$\text{Subtraction:} \quad A_1 \ominus A_2 = (a_1 - c_2, b_1 - b_2, c_1 - a_2) \tag{3}$$

Multiplication: if k is a scalar

$$k \otimes A_1 = \begin{cases} (ka_1, kb_1, kc_1), & k > 0 \\ (kc_1, kb_1, ka_1), & k < 0 \end{cases}$$

$$A_1 \otimes A_2 \approx (a_1a_2, b_1b_2, c_1c_2), \quad \text{if} \quad a_1 \geq 0, a_2 \geq 0 \tag{4}$$

$$\text{Division: } A_1 \oslash A_2 \approx \left(\frac{a_1}{c_2}, \frac{b_1}{b_2}, \frac{c_1}{a_2}\right), \quad \text{if} \quad a_1 \geq 0, a_2 \geq 0 \tag{5}$$

Although multiplication and division operations on triangular fuzzy numbers do not necessarily yield a triangular fuzzy number, triangular fuzzy number approximations can be used for many practical applications (Kaufmann & Gupta, 1988). Triangular fuzzy numbers are appropriate for quantifying the vague information about most decision problems including personnel selection (e.g. rating for creativity, personality, leadership, etc.). The primary reason for using triangular fuzzy numbers can be stated as their intuitive and computational-efficient representation (Karsak, 2002).

A linguistic variable is defined as a variable whose values are not numbers, but words or sentences in natural or artificial language. The concept of a linguistic variable appears as a useful means for providing approximate characterization of phenomena that are too complex or ill defined to be described in conventional quantitative terms (Zadeh, 1975).

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3. The Fuzzy TOPSIS Method

This study uses this method to select the best adequate person. TOPSIS views a MADM problem with *m* alternatives as a geometric system with *m* points in the *n*-dimensional space. The method is based on the concept that the chosen alternative should have the shortest distance from the positive-ideal solution and the longest distance from the negative-ideal solution. TOPSIS defines an index called similarity to the positive-ideal solution and the remoteness from the negative-ideal solution. Then the method chooses an alternative with the maximum similarity to the positive-ideal solution (Wang & Chang, 2007). It is often difficult for a decision-maker to assign a precise performance rating to an alternative for the attributes under consideration. The merit of using a fuzzy approach is to assign the relative importance of attributes using fuzzy numbers instead of precise numbers. This section extends the TOPSIS to the fuzzy environment (Yang & Hung, 2007). This method is particularly suitable for solving the group decision-making problem under fuzzy environment. We briefly review the rationale of fuzzy theory before the development of fuzzy TOPSIS. The mathematics concept borrowed from Ashtiani, Haghighirad, Makui, and Montazer (2008), (Büyüközkan et al., 2007) and (Wang and Chang, 2007).

Step 1: Determine the weighting of evaluation criteria

A systematic approach to extend the TOPSIS is proposed to selecting best person under a fuzzy environment in this section. In this paper the importance weights of various criteria and the ratings of qualitative criteria are considered as linguistic variables (as Table 1) (Chen, Lin, & Huang, 2006).

Table 1. Linguistic scales for the importance of each criterion.

Linguistic variable	Corresponding triangular fuzzy number
Very low (VL)	(0.0, 0.1, 0.3)
Low (L)	(0.1, 0.3, 0.5)
Medium (M)	(0.3, 0.5, 0.7)
High (H)	(0.5, 0.7, 0.9)
Very high (VH)	(0.7, 0.9, 1.0)

Step 2: Construct the fuzzy decision matrix and choose the appropriate linguistic variables for the alternatives with respect to criteria

$$\tilde{D} = \begin{array}{c c} & \begin{array}{cccc} C_1 & C_2 & \cdots & C_N \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_M \end{array} & \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix} \end{array} \quad i=1,2,\ldots,m;\ j=1,2,\ldots,n$$

$$\tilde{x}_{ij} = \frac{1}{k}(\tilde{x}_{ij}^{1} + \tilde{x}_{ij}^{2} + \ldots + \tilde{x}_{ij}^{k}) \tag{6}$$

where $\tilde{x}_{ij}^{k}$ is the rating of alternative A_i with respect to criterion C_j evaluated by K expert and $\tilde{x}_{ij}^{k} = (a_{ij}^{k}, b_{ij}^{k}, c_{ij}^{k})$

Step 3: Normalize the fuzzy decision matrix

The normalized fuzzy decision matrix denoted by $\tilde{R}$ is shown as following formula:

$$\tilde{R} = [\tilde{r}_{ij}]_{m\times n},\ i= 1,2,\ldots,m;\ j=1,2,\ldots,n \tag{7}$$

Then the normalization process can be performed by following formula:

Where $\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^{+}}, \frac{b_{ij}}{c_j^{+}}, \frac{c_{ij}}{c_j^{+}}\right)$ $c_j^{+} = \max_i c_{ij}$

The normalized $\tilde{r}_{ij}$ are still triangular fuzzy numbers. For trapezoidal fuzzy numbers, the normalization process can be conducted in the same way. The weighted fuzzy normalized decision matrix is shown as following matrix $\tilde{V}$:

$$\tilde{v} = [\tilde{v}_{ij}]_{m\times n},\ i= 1,2,\ldots,m;\ j=1,2,\ldots,n \tag{8}$$

$$\tilde{v}_{ij} = \tilde{r}_{ij} \otimes \tilde{w}_j \tag{9}$$

Step 4: Determine the fuzzy positive-ideal solution (FPIS) and fuzzy negative-ideal solution (FNIS)

According to the weighted normalized fuzzy decision matrix, we know that the elements $\tilde{V}_{ij}$ are normalized positive TFNs and their ranges belong to the closed interval [0, 1]. Then, we can define the FPIS A^{+} and FNIS A^{-} as following formula:

$$A^{+} = (\tilde{V}_1^{+}, \tilde{V}_2^{+}, \ldots, \tilde{V}_n^{+}) \tag{10}$$

$A^- = (\tilde{V}_1^-, \tilde{V}_2^-, \ldots, \tilde{V}_n^-)$ (11)

where $\tilde{V}_j^+ = (1,1,1)$ and $\tilde{V}_j^- = (0,0,0)$ j=1,2,…,n

Step 5: Calculate the distance of each alternative from FPIS and FNIS

The distances (d_i^+ and d_i^-) of each alternative A^+ from and A^- can be currently calculated by the area compensation method.

$$d_i^+ = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{V}_j^+), \quad i=1,2,\ldots,m \quad j=1,2,\ldots,n \tag{12}$$

$$d_i^- = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{V}_j^-), \quad i=1,2,\ldots,m \quad j=1,2,\ldots,n \tag{13}$$

Step 6: Obtain the closeness coefficient (CC) and rank the order of alternatives

The CC_i is defined to determine the ranking order of all alternatives once the d_i^+ and d_i^- of each alternative have been calculated. Calculate similarities to ideal solution. This step solves the similarities to an ideal solution by formula:

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-} \quad i=1,2,\ldots,m \tag{14}$$

According to the CC_i, we can determine the ranking order of all alternatives and select the best one from among a set of feasible alternatives.

In the last years, some fuzzy TOPSIS methods were developed in the different applied field. Lin and Chang (2008) adopted fuzzy TOPSIS for order selection and pricing of manufacturer (supplier) with make-to-order basis when orders exceed production capacity. Chen and Tsao (2008) are to extend the TOPSIS method based on interval-valued fuzzy sets in decision analysis. Ashtiani et al. (2008) used interval-valued fuzzy TOPSIS method is aiming at solving MCDM problems in which the weights of criteria are unequal, using interval-valued fuzzy sets concepts. Mahdavi, Mahdavi-Amiri, Heidarzade, and Nourifar (2008) designed a model of TOPSIS for the fuzzy environment with the introduction of appropriate negations for obtaining ideal solutions. Büyüközkan et al. (2007) identified the strategic main and sub-criteria of alliance partner selection that companies consider the most important through Fuzzy AHP and fuzzy TOPSIS model and achieved the final partner-ranking results. Abo-Sinna, Amer, and Ibrahim (2008) focused on multi-objective large-scale non-linear programming problems with block angular structure and extended the technique for order preference by similarity ideal solution to solve them. Wang and Chang (2007) applied fuzzy

TOPSIS to help the Air Force Academy in Taiwan choose optimal initial training aircraft in a fuzzy environment. Li (2007) developed a compromise ratio (CR) methodology for fuzzy multi-attribute group decision making (FMAGDM), which is an important part of decision support system. Wang and Lee (2007) generalized TOPSIS to fuzzy multiple-criteria group decision-making (FMCGDM) in a fuzzy environment. Kahraman, Çevik, Ates, and Gülbay (2007) proposed a fuzzy hierarchical TOPSIS model for the multi-criteria evaluation of the industrial robotic systems. Benı´tez, Martı´n, and Román (2007) presented a fuzzy TOPSIS approach for evaluating dynamically the service quality of three hotels of an important corporation in Gran Canaria island via surveys. Wang and Elhag (2006) proposed a fuzzy TOPSIS method based on alpha level sets and presents a non-linear programming solution procedure. Chen et al. (2006) applied fuzzy TOPSIS approach to deal with the supplier selection problem in supply chain system.

4. Personnel selecting using fuzzy TOPSIS approach

In this research, 12 experts and managers were invited to survey four alternatives using the research framework shown in Fig 2. Through the literature investigation and experts' opinions, the committee finally adopted 12 criteria. This research framework includes 12 evaluation criteria, such as Analytical thinking (C_1), Bachelor or Master Degree (C_2), Work experience (C_3), foreign language (C_4), Willingness (C_5), Effective time using (C_6), Decision making (C_7), Working in teams (C_8), Appearance candidates (C_9), Age (C_{10}), Culture (C_{11}) and Core ability (C_{12}). In addition, there are four alternatives include: person number one (P_1), (P_2), (P_3) and (P_4).

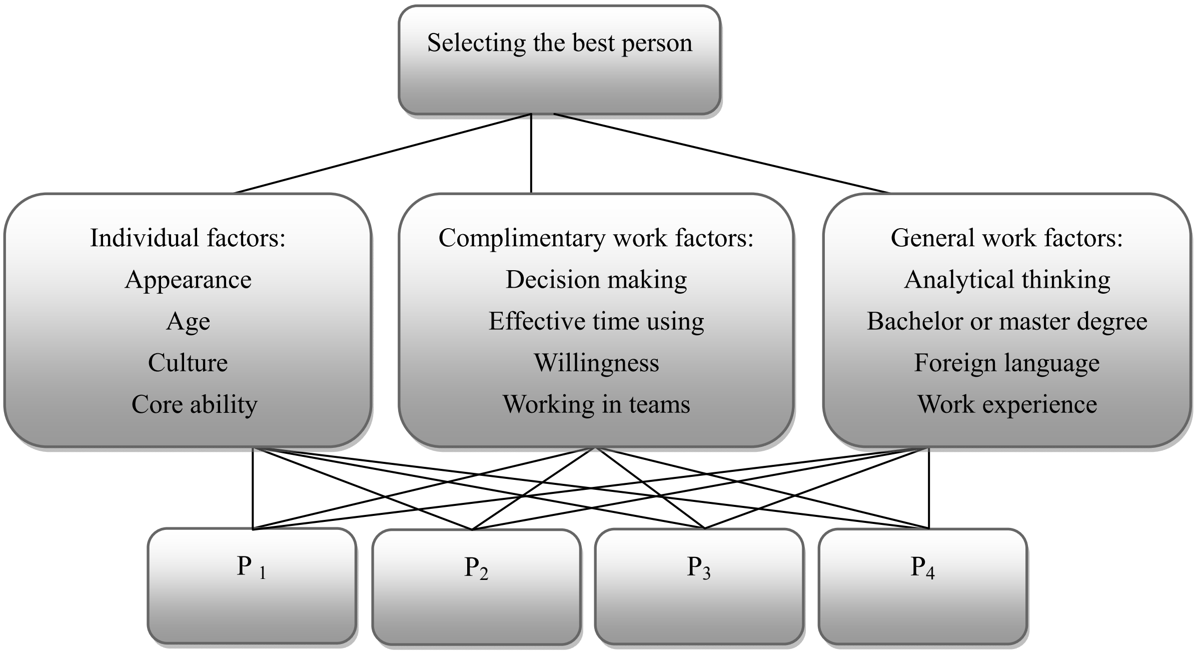

Figure 2. Research framework

After the construction of the hierarchy the different priority weights of each criteria, attributes and alternatives are calculated using the fuzzy TOPSIS approach. The comparison of the importance or preference of one criterion, attribute or alternative over another can be done with the help of the questionnaire. The method of calculating priority weights of the different decision alternatives is discussed following part.

Step 1: Determine the linguistic weighting of each criteria

We adopt fuzzy TOPSIS method to evaluate the weights of different criteria for selecting the best person. Following the construction of fuzzy TOPSIS model, it is extremely important that experts fill the judgment matrix. From the viewpoint of expert validity, the buildup of most of the operationalizations was based on the literature that caused them to have expert validity. The result of the fuzzy decision reached by each alternative is a fuzzy number and the average fuzzy numbers is shown in the second column in Table 2. Therefore, it is necessary that a non fuzzy ranking method for fuzzy numbers be employed for comparison of each alternative. In other words, the procedure of defuzzification is to locate the Best Non fuzzy Performance value (BNP). Methods of such defuzzified fuzzy ranking generally include mean of maximal (MOM), center of area (COA), and a-cut. The COA method to find out the BNP is a simple and practical method, so it is used in this study.

To take the BNP value of the weight of C_1 as an example, the calculation process is as follows:

$$BNP_{w_1} = [(U_{w_1} - L_{w_1}) + (M_{w_1} - L_{w_1})]/3 + L_{w_1} = [(0.94-0.58)+(0.78-0.58)]/3+0.58=0.769 \quad (15)$$

Then, the weights for the remaining dimensions can be found as shown in Table 2. Table 2 shows the relative weight of criteria, which obtained by fuzzy TOPSIS method. The weights for each criterion are: C_1 (0.769), C_2 (0.767), C_3 (0.750), C_4 (0.703), C_5 (0.489), C_6 (0.733), C_7 (0.806), C_8 (0.781), C_9 (0.597), C_{10} (0.716), C_{11} (0.711) and C_{12} (0.711). From the fuzzy TOPSIS results, we can understand the first two important factors for selecting person are C_7 (0.806) and C_8 (0.781). Moreover, the less important factor is C_5 (0.489).

Table 2. Weights of each criterion

		BNP	Rank
C_1	(0.58, 0.78, 0.94)	0.769	3
C_2	(0.58, 0.78, 0.93)	0.767	4
C_3	(0.57, 0.77, 0.92)	0.750	5
C_4	(0.52, 0.72, 0.88)	0.703	10
C_5	(0.31, 0.48, 0.68)	0.489	12
C_6	(0.55, 0.75, 0.90)	0.733	6
C_7	(0.63, 0.83, 0.95)	0.806	1
C_8	(0.60, 0.80, 0.94)	0.781	2
C_9	(0.40, 0.60, 0.79)	0.597	11
C_{10}	(0.55, 0.75, 0.85)	0.716	7
C_{11}	(0.53, 0.73, 0.88)	0.711	8
C_{12}	(0.53, 0.73, 0.88)	0.711	9

Step 2: Estimating the performance

This paper focus on determining the best person; so, we assume that questionnaire have collected completely and will start with building dataset that are collected. The evaluators have their own range for the linguistic variables employed in this study according to their subjective judgments (Hsieh, Lu, & Tzeng, 2004).

For each evaluator with the same importance, this study employs the method of average value to integrate the fuzzy/vague judgment values of different evaluators regarding the same evaluation dimensions. The evaluators then adopted linguistic terms (see Table 3), including "very poor", "poor", "fair", "good" and "very good" to express their opinions about the rating of every person, based on the fuzzy data of the four person listed in Table 4.

Table 3. Linguistic scales for the rating of each cluster policy

Linguistic variable	Corresponding triangular fuzzy number
Very poor (VP)	(0, 1, 3)
Poor (P)	(1, 3, 5)
Fair (F)	(3, 5, 7)
Good (G)	(5, 7, 9)
Very good (VG)	(7, 9, 10)

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Table 4. Subjective cognition results of evaluators towards the five levels of linguistic variables

	A_1	A_2	A_3	A_4
C_1	(5.33, 7.33, 9.17)	(4.50, 6.50, 8.42)	(3.25, 5.17, 7.17)	(2.67, 4.67, 6.67)
C_2	(4.50, 6.50, 8.42)	(4.83, 6.83, 8.67)	(3.17, 5.17, 7.17)	(3.00, 5.00, 7.00)
C_3	(4.33, 6.33, 8.33)	(4.67, 6.67, 8.58)	(3.08, 5.00, 7.00)	(2.83, 4.83, 6.83)
C_4	(4.67, 6.67, 8.67)	(4.00, 6.00, 8.00)	(3.17, 5.17, 7.17)	(2.45, 4.45, 6.45)
C_5	(3.50, 5.50, 7.50)	(3.50, 5.50, 7.42)	(2.42, 4.33, 6.33)	(2.17, 4.17, 6.17)
C_6	(4.67, 6.67, 8.42)	(3.50, 5.33, 7.33)	(2.50, 4.33, 6.33)	(2.08, 4.00, 6.00)
C_7	(4.17, 6.17, 8.17)	(4.00, 6.00, 7.92)	(2.92, 4.83, 6.83)	(2.67, 4.67, 6.67)
C_8	(4.17, 6.17, 8.17)	(3.83, 5.83, 7.75)	(3.00, 5.00, 7.00)	(2.17, 4.17, 6.17)
C_9	(4.83, 6.83, 8.67)	(4.67, 6.67, 8.58)	(3.83, 5.83, 7.83)	(1.75, 3.50, 5.50)
C_{10}	(4.67, 6.67, 8.58)	(4.33, 6.33, 8.25)	(3.00, 5.00, 7.00)	(1.67, 3.50, 5.50)
C_{11}	(5.17, 7.17, 9.00)	(4.67, 6.67, 8.50)	(3.50, 5.50, 7.50)	(1.83, 3.67, 5.67)
C_{12}	(4.50, 6.50, 8.42)	(4.08, 6.00, 7.83)	(3.17, 5.17, 7.17)	(2.17, 4.00, 6.00)

Step 3: Normalize the fuzzy decision matrix

Using Eq. (7), we can normalize the fuzzy decision matrix as Table 5.Table 5. Normalized fuzzy decision matrix

	A_1	A_2	A_3	A_4
C_1	(0.58, 0.80, 1.00)	(0.52, 0.75, 0.97)	(0.41, 0.66, 0.91)	(0.38, 0.67, 0.95)
C_2	(0.49, 0.71, 0.92)	(0.56, 0.79, 1.00)	(0.40, 0.66, 0.91)	(0.43, 0.71, 1.00)
C_3	(0.47, 0.69, 0.91)	(0.54, 0.77, 0.99)	(0.39, 0.64, 0.89)	(0.40, 0.69, 0.98)
C_4	(0.51, 0.73, 0.95)	(0.46, 0.69, 0.92)	(0.40, 0.66, 0.91)	(0.35, 0.64, 0.92)
C_5	(0.38, 0.60, 0.82)	(0.40, 0.63, 0.86)	(0.31, 0.55, 0.81)	(0.31, 0.60, 0.88)
C_6	(0.51, 0.73, 0.92)	(0.40, 0.62, 0.85)	(0.32, 0.55, 0.81)	(0.30, 0.57, 0.86)
C_7	(0.45, 0.67, 0.89)	(0.46, 0.69, 0.91)	(0.37, 0.62, 0.87)	(0.38, 0.67, 0.95)
C_8	(0.45, 0.67, 0.89)	(0.44, 0.67, 0.89)	(0.38, 0.64, 0.89)	(0.31, 0.60, 0.88)
C_9	(0.53, 0.75, 0.95)	(0.54, 0.77, 0.99)	(0.49, 0.74, 1.00)	(0.25, 0.50, 0.79)
C_{10}	(0.51, 0.73, 0.94)	(0.50, 0.73, 0.95)	(0.38, 0.64, 0.89)	(0.24, 0.50, 0.79)
C_{11}	(0.56, 0.78, 0.98)	(0.54, 0.77, 0.98)	(0.45, 0.70, 0.96)	(0.26, 0.52, 0.81)
C_{12}	(0.49, 0.71, 0.92)	(0.47, 0.69, 0.90)	(0.40, 0.66, 0.91)	(0.31, 0.57, 0.86)

Step 4: Establish the weighted normalized fuzzy decision matrix

The forth step in the analysis is to find the weighted fuzzy decision matrix, and the resulting

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fuzzy weighted decision matrix is shown as Table 6. The lower bound of C_1 for A_1 in Table 6 (.34) is equal to the lower bound of C_1 for A_1 in Table 5 (.58) multiplied by lower bound of C_1 in Table 2 (.58).Table 6 .Weighted normalized fuzzy decision matrix

	A_1	A_2	A_3	A_4
C_1	(0.34, 0.63, 0.94)	(0.30, 0.59, 0.93)	(0.24, 0.52, 0.92)	(0.22, 0.52, 0.88)
C_2	(0.29, 0.56, 0.86)	(0.33, 0.62, 0.93)	(0.24, 0.52, 0.85)	(0.25, 0.56, 0.93)
C_3	(0.27, 0.53, 0.83)	(0.31, 0.59, 0.91)	(0.22, 0.49, 0.82)	(0.23, 0.53, 0.89)
C_4	(0.26, 0.52, 0.83)	(0.24, 0.50, 0.81)	(0.21, 0.47, 0.80)	(0.18, 0.46, 0.81)
C_5	(0.12, 0.29, 0.55)	(0.12, 0.31, 0.58)	(0.10, 0.27, 0.55)	(0.10, 0.29, 0.59)
C_6	(0.28, 0.55, 0.83)	(0.22, 0.46, 0.76)	(0.18, 0.41, 0.73)	(0.16, 0.43, 0.77)
C_7	(0.29, 0.56, 0.85)	(0.29, 0.58, 0.87)	(0.24, 0.51, 0.83)	(0.24, 0.56, 0.90)
C_8	(0.27, 0.54, 0.84)	(0.27, 0.54, 0.84)	(0.23, 0.51, 0.84)	(0.19, 0.48, 0.83)
C_9	(0.21, 0.45, 0.75)	(0.22, 0.46, 0.78)	(0.20, 0.45, 0.79)	(0.10, 0.30, 0.62)
C_{10}	(0.28, 0.54, 0.80)	(0.28, 0.55, 0.81)	(0.21, 0.48, 0.76)	(0.13, 0.37, 0.67)
C_{11}	(0.30, 0.57, 0.86)	(0.29, 0.56, 0.86)	(0.24, 0.51, 0.84)	(0.14, 0.38, 0.71)
C_{12}	(0.26, 0.510, 0.81)	(0.25, 0.50, 0.79)	(0.21, 0.48, 0.80)	(0.16, 0.42, 0.75)

Step 5: Determine the fuzzy positive and fuzzy negative-ideal reference points

Then we can define the fuzzy positive-ideal solution (FPIS) and the fuzzy negative-ideal solution (FNIS) as: $A^+$and A^-. This is the fifth step of the fuzzy TOPSIS analysis.

A^+ = [(1,1,1) , (1,1,1), (1,1,1), (1,1,1), (1,1,1), (1,1,1)]

A^- = [(0,0,0) ,(0,0,0) ,(0,0,0) ,(0,0,0) ,(0,0,0) ,(0,0,0)]

Step 6: ranking the alternatives

In order to calculate the closeness coefficients of each of the alternatives d_i^+ and d_i^- calculation is used as an example as follows.

Once the distances of cluster policy from FPIS and FNIS are determined, the closeness coefficient can be obtained with Eq. (14). The index CC_1 of first alternative is calculated as:

d_i^+ = 6.248 d_i^- = 6.926

From the alternative evaluation results in Table 7, the best person is the second person (P_2).

$$CC_1 = \frac{6.926}{6.248+6.926} = 0.526$$

$CC_2 \succ CC_1 \succ CC_3 \succ CC_4$

Table 7. Closeness coefficients and ranking

	d_i^+	d_i^-	CC_i	Rank
P_1	6.248	6.926	0.526	2
P_2	6.264	6.985	0.527	1
P_3	6.779	6.550	0.491	3
P_4	7.103	6.330	0.471	4

5. Conclusion

In this age of increased competitive markets, the notion of the personnel selection problem has an enormous interest. Decisions makers face rising and complex environments today, and also decision makers are often uncertain in assigning the evaluation scores in crisp value. Therefore, in this paper, we tried to design a multi-criteria decision-making model based on fuzzy set theory to select the most adequate person. Unlike other decision methods, the proposed model can adaptively find a suitable person for the job. For making uniform consensus of the decision makers, we converted all pair-wise comparisons into triangular fuzzy numbers to adjust fuzzy rating and fuzzy attribute weight, and used fuzzy operators to get to select the best alternative.

Finally, observing all these results, Fuzzy TOPSIS approach propose alternative (P_2) as the best choice and P_1, P_3 , P_4 are the second, third and fourth choice.

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