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A fuzzy hybrid MCDM approach for professional selection

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ABSTRACT

Personnel selection is an important process in management. Sniper selection as a subset of personnel selection contains different characteristics compared to selection of other personnel. The multi criteria nature and the presence of both qualitative and quantitative factors make it considerably more complex. This study proposes a fuzzy hybrid multicriteria decision making approach enabling the combination of both qualitative and quantitative factors. The use of a combination of Fuzzy ANP, Fuzzy TOPSIS, Fuzzy ELECTRE techniques, proposing a MCDM approach for sniper selection, and applying these to a real case are the unique features of this study.

1. Introduction

Personnel selection is the process of choosing individuals who match the qualifications required to perform a defined job in the best possible way (Dursun & Karsak, 2009). Accurate personnel selection, taking into account the company circumstances, allows managers to optimize production costs and achieve corporative goals (Canos & Liern, 2008). A great deal of attention in the literature has been given for the selection of the most eligible and suitable candidate among alternatives, and extensively conducted reviews can be found in Robertson and ve Smith (2001). The objective of a selection process depends mainly on assessing the differences among candidates and predicting future performance (Güngör, Serhadlıoğlu, & Kesen, 2009). Robertson and ve Smith (2001) described commonly used personnel selection process as:

- Detailed analysis of the job, leading to.
- An indication of the psychological attributes required of a successful candidate.
- Personnel selection methods aim to assess the extent to which these attributes are possessed by candidates.
- A validation process tracks the success of the selection process in identifying suitable candidates.

As in many decision problems, personnel selection problem is extremely complex in real life; humans generally fail to make a good prediction for quantitative problems, in contrast they may make accurate guesses in qualitative forecasting. Because of the imprecise expressions, a fuzzy approach is commonly used in decision problems. Fuzzy linguistic models permit the translation of verbal expressions into numerical ones. Thereby, when dealing quantitatively with imprecision in the expression of the importance of each criterion, some multi-criteria methods based on fuzzy relations are used (Güngör et al., 2009).

In this study, a fuzzy hybrid multi criteria decision making (MCDM) method is adapted to personnel selection. A fuzzy analytic network process (FANP) is conducted to address the problem of dependence as well as feedback among each measurement criteria. A technique for order preference by similarity to an ideal solution (TOPSIS) and ELECTRE (ELimination Et Choix Traduisant la REalité) are finally utilized to find optimal alternatives for personnel selection. Here, we combine Fuzzy ANP and Fuzzy TOPSIS approaches to develop a more accurate personnel selection methodology. For an illustrative example proposed model is conducted on sniper selection process. The organization of the paper is as follows: first, personnel selection and used MCDM methods are reviewed. Second, the review on FANP, Fuzzy TOPSIS and Fuzzy ELECTRE will be given. Following this, a professional selection model is demonstrated and performed as an illustrative example.

2. MCDM methods for personnel selection

In real-world cases most problems have more than one decision criterion. So MCDM methods have been developed to solve complex problems. The aim in MCDM is to determine overall preferences among alternative options. According to the objective, MCDM methods can be used for outranking alternatives or final decision of choice.

Among the MCDM problems encountered in real life is that of personnel selection, and from the multi-criteria perspective, this

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has attracted the interest of many scholars (Kelemenis & Askounis, 2010). Kelemenis and Askounis (2010) used a new TOPSIS-based multi-criteria approach to personnel selection. They utilized fuzzy-TOPSIS with veto threshold.

Jessop (2004) applied minimally biased weight determination for personnel selection. He used two methods and found that both were feasible. Lazarevic-Petrovic (2001) aimed to provide an approach to minimizing subjective judgments in the crucial procedures of personnel selection: short-listed procedure and hiring decision procedure. She used a two-level personnel selection fuzzy model in her article.

Dursun and Karsak (2009) developed a fuzzy multi-criteria decision making algorithm using the principles of fusion of fuzzy information, 2-tuple linguistic representation model, and technique for order preference by similarity to ideal solution (TOPSIS) in their article for personnel selection. Güngör et al. (2009) proposed a personnel selection system based on fuzzy analytic hierarchy process. In their study, fuzzy analytic hierarchy process is applied in order to evaluate the best personnel, dealing with the rating of both qualitative and quantitative criteria.

Canos and Liern (2008) demonstrated an aggregation model based on efficiency analysis used to order the candidate. They developed a flexible decision support system, which simulates experts' evaluations using ordered weighted average (OWA) aggregation operators, to help managers in their decision-making functions.

Chen and Cheng (2005) proposed to rank fuzzy numbers by metric distance and a computer –based Group Decision Support System (GDSS) has been developed to solve the IS personnel selection problem. Gibney and Shang (2007) described the use of analytic hierarchy process in the dean selection process, and found that AHP provided a convenient and effective tool for evaluating personnel.

Celik and Kandakoglu Ahmet ve Er Deha (2009) proposed a fuzzy integrated multi-stage evaluation model under multiple criteria in order to manage the academic personnel selection and development processes in Maritime Education and Training institutions. Their proposal consisted of fuzzy analytic hierarchy process and fuzzy TOPSIS under multiple criteria.

Karsak (2000) presented a fuzzy multiple objective approaches for personnel selection. He presented the fuzzy multi-objective Boolean linear programming formulation. Liang and Wang (1994) presented a fuzzy multi-criteria decision making algorithm for personnel selection.

Chen, Hwang, and Hung (2009) used a multiple linguistic PROMETHEE method for personnel selection and evaluation. They used crisp value to express quantitative information and used 2-tuple linguistic value to express qualitative information.

Wang (2009) applied grey theory and MCDM method to the R&D personnel selection problem. In his research, TOPSIS was utilized as MCDM method. The weight and rating of attributes for all alternatives were described by linguistic variables that can be expressed in interval grey number. Then grey relational grade was proposed to determine ranking order of all alternatives. Ayub, Kabir, and Alam (2009) used analytic network process (ANP) under fuzzy environment. Table 1 summarizes the methods used for personnel selection.

3. Fuzzy ANP

The analytic hierarchy method (ANP) allows for complex interrelationships among decision levels and attributes (Saaty, 1996). The ANP feedback approach replaces hierarchies (Fig. 1a) with networks (Fig. 1b) in which the relationships between levels cannot be easily represented as higher or lower, dominant or subordinate, direct or indirect (Meade & Sarkis, 1999).

Table 1
Methods used for personnel selection.

References	Methods
Wang (2009)	Grey System and TOPSIS
Chen et al. (2009)	2-tuple linguistic variable, PROMETHEE
Karsak (2000)	Fuzzy Multi-Objective Boolean Linear Programming
Celik and Kandakoglu Ahmet ve Er Deha (2009)	Fuzzy AHP and Fuzzy TOPSIS
Gibney and Shang (2007)	AHP
Chen and Cheng (2005)	Fuzzy GDSS
Canos and Liern (2008)	OWA under Fuzzy Environment
Güngör et al. (2009) and Lazarevic-Petrovic (2001)	Fuzzy AHP
Dursun and Karsak (2009)	Fuzzy TOPSIS (2-tuple linguistic variables)
Jereb, Rajkovic, and Rajkovic (2005)	Hierarchical Multi-Attribute System Approach (Dexi Tool)
Jessop (2004)	Minimally Biased Weighted Multiple Criteria Analysis
Gargano Michael, Marose Robert, and von Kleeck (1991)	Artificial Neural Networks and Genetic Algorithm
Kelemenis and Askounis (2010)	Fuzzy TOPSIS with veto threshold
Ayub et al. (2009)	Fuzzy ANP
Shih, Huang, and Shyur (2005)	GDSS

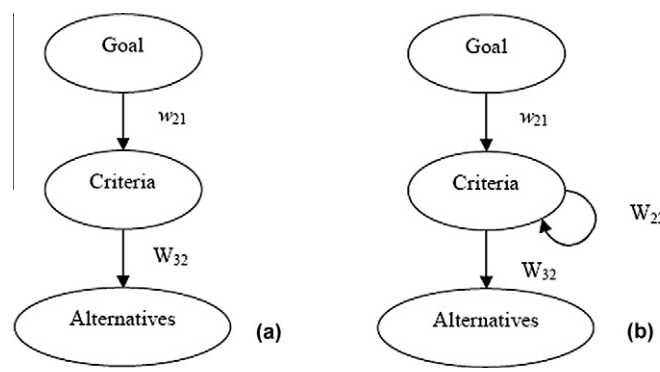

Fig. 1. Hierarchy and network: (a) hierarchy; (b) network (Chung et al., 2006; Momoh & Zhu, 2003).

In ANP, the modeling process can be divided to three steps, which are described as follows (Onut, Kara, & Isık, 2009):

Step 1: the pairwise comparisons and relative weight estimation.
Before performing the pairwise comparisons, all criteria and clusters compared are linked to each other. The pairwise comparisons are made depending on the scale shown in Table 2. In the pairwise comparison matrix, the score of a_{ij} represents the relative importance of the component on row (i) over the component on column (j), i.e., $a_{ij} = w_i/w_j$. The reciprocal value of the expression ($1/a_{ij}$) is used when the component j is more

Table 2
Comparison scale.

Linguistic scale for importance	Linguistic scale for performance	Triangular fuzzy scale	Triangular fuzzy reciprocal scale
Equal importance	Very poor	1, 1, 1	1, 1, 1
Weak importance (of one over the other)	Poor	2, 3, 4	1/4, 1/3, 1/2
Strong importance	Fair	4, 5, 6	1/6, 1/5, 1/4
Demonstrated importance over the other	Good	6, 7, 8	1/8, 1/7, 1/6
Absolute importance	Very good	8, 9, 10	1/10, 1/9, 1/8

important than the component i. The comparison matrix A is defined as

$$A = \begin{bmatrix} w_1/w_1 & w_1/w_2 & \cdots & w_1/w_n \\ w_2/w_1 & w_2/w_2 & \cdots & w_2/w_n \\ \vdots & \vdots & & \vdots \\ w_n/w_1 & w_n/w_2 & \cdots & w_n/w_n \end{bmatrix} = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ 1/a_{12} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & & \vdots \\ 1/a_{1n} & 1/a_{2n} & \cdots & 1 \end{bmatrix}. \tag{1}$$

Then, a local priority vector (eigenvector) w is computed as an estimate of the relative importance accompanied by the elements being compared by solving the following equation:

$$Aw = \lambda_{\max} w, \tag{2}$$

where $\lambda_{\max}$ is the largest eigenvalue of matrix A.

Step 2: formation of the initial supermatrix.

The obtained vectors are further normalized to represent the local weight vector. Supermatix is formed, local weight vectors are entered in the appropriate columns of the matrix of influence among the elements, to obtain global priorities (Onut et al., 2009; Saaty & Vargas, 1998). The supermatrix representation of a network with three levels is given as follows (Fig. 1b):

$$W = \begin{array}{l} \\ \mathit{Goal}\ (G) \\ \mathit{Criteria}\ (C) \\ \mathit{Alternatives}\ (A) \end{array} \begin{array}{c} \quad G \qquad C \qquad A \\ \begin{pmatrix} 0 & 0 & 0 \\ W_{21} & W_{22} & 0 \\ 0 & W_{32} & I \end{pmatrix} \end{array} \tag{3}$$

W_{21} is a vector that represents the impact of the goal on the criteria, W_{22} is a vector that represents impact of the interdependences among criteria, W_{32} is also a vector that represents the impact of criteria on each of alternatives, and I is the identity matrix. Any zero value in the super-matrix can be replaced by a matrix if there is an interrelationship of elements within a cluster or between to clusters.

Step 3: formation of the weighted super-matrix.

An eigenvector is obtained from the pair-wise comparison matrix of the row clusters with respect to the column cluster, which in turn yields an eigenvector for each column cluster. The first entry of the respective eigenvector for each column cluster is multiplied by all the elements in the first cluster of that column, the second by all the elements in the second cluster of that column and so on. In this way, the cluster in each column of the supermatrix is weighted, and the result, known as the weighted super-matrix, is stochastic (Yüksel & Dagdeviren, 2007).

DM cannot always explain his judgments about certain attributes, physical situations, being healthy, etc., with discrete scales. For these reasons fuzzy scales are defined. In the application, triangle fuzzy numbers, Table 2, have been used by DM to state their preferences to compare attributes.

In the proposed methodology, pair-wise comparison matrices are formed with the help of triangle fuzzy numbers, the fuzzy ANP (FANP) has been used to solve the problem of professional selection. The FANP can easily accommodate the interrelationships existing among the functional activities. The concept of supermatrices is employed to obtain the composite weights that overcome the existing interrelationships (Mohanty, Agarwal, Choudhury, & Tiwari, 2005; Onut et al., 2009).

Pairwise comparison matrices are structured by using triangle fuzzy numbers (l,m,u).

The fuzzy matrix can be given as follows (Onut et al., 2009):

$$\widetilde{A} = \begin{pmatrix} (a_{11}^l, a_{11}^m, a_{11}^u) & (a_{12}^l, a_{12}^m, a_{12}^u) & \cdots & (a_{1n}^l, a_{1n}^m, a_{1n}^u) \\ (a_{21}^l, a_{21}^m, a_{21}^u) & (a_{22}^l, a_{22}^m, a_{22}^u) & \cdots & (a_{2n}^l, a_{2n}^m, a_{2n}^u) \\ \vdots & \vdots & \vdots & \vdots \\ (a_{m1}^l, a_{m1}^m, a_{m1}^u) & (a_{m1}^l, a_{m1}^m, a_{m1}^u) & \cdots & (a_{mn}^l, a_{mn}^m, a_{mn}^u) \end{pmatrix}. \tag{4}$$

The a_{mn} represents the of comparison m (row) with component n (column). The pair-wise comparison matrix $(\widetilde{A})$ is assumed as reciprocal

$$\widetilde{A} = \begin{pmatrix} (1,1,1) & (a_{12}^l, a_{12}^m, a_{12}^u) & \cdots & (a_{1n}^l, a_{1n}^m, a_{1n}^u) \\ \left(\frac{1}{a_{12}^u}, \frac{1}{a_{12}^m}, \frac{1}{a_{12}^l}\right) & (1,1,1) & \cdots & (a_{2n}^l, a_{2n}^m, a_{2n}^u) \\ \vdots & \vdots & \vdots & \vdots \\ \left(\frac{1}{a_{1n}^u}, \frac{1}{a_{1n}^m}, \frac{1}{a_{1n}^l}\right) & \left(\frac{1}{a_{2n}^u}, \frac{1}{a_{2n}^m}, \frac{1}{a_{2n}^l}\right) & \cdots & (1,1,1) \end{pmatrix}. \tag{5}$$

In this study, logarithmic least squares method is used for getting estimates for fuzzy priorities $\tilde{w}_i$ (Chen, Hwang, & Hwang, 1992). ANP can be used to calculate the relative importance of the criteria and outrank the alternatives. In our proposed model, FANP will be used only to calculate the triangular fuzzy weights for the relative importance of the criteria and the interdependence priorities of the criteria (Eq. (6)) will be used to support fuzzy TOPSIS and ELECTRE for outranking the alternatives.

$$W = \begin{pmatrix} 0 & 0 \\ W_{21} & W_{22} \end{pmatrix}. \tag{6}$$

The logarithmic least squares method for calculating triangular fuzzy weights can be given as follows (Ramik, 2006):

$$\widetilde{W} = \left(W_k^l, W_k^m, W_k^u\right) \quad k = 1,2,3,\ldots,n, \tag{7}$$

where

$$W_k^s = \frac{\left(\prod_{j=1}^n a_{kj}^s\right)^{1/n}}{\sum_{i=1}^n \left(\prod_{j=1}^n a_{ij}^m\right)^{1/n}}, \quad s \in \{l,m,u\}. \tag{8}$$

4. Fuzzy TOPSIS

TOPSIS is based on the concept that the most preferred alternative should not only have the shortest distance from the positive ideal solution, but also have the longest distance from the negative ideal solution (Hwang & Yoon, 1981). According to this technique, the best alternative would be the one that is nearest to the positive-ideal solution and farthest from the negative ideal solution (Ertugrul & Karakasoglu, 2009).

Definition 1. Let $\tilde{a} = (a_1, a_2, a_3)$ and $\tilde{b} = (b_1, b_2, b_3)$ be two triangular fuzzy numbers. Then the distance between them can be calculated by using the vertex method as (Chen, 2000):

$$d(\tilde{a}, \tilde{b}) = \sqrt{\frac{1}{3}[(a_1 - b_1)^2 + (a_2 - b_2)^2 + (a_3 - b_3)^2]}. \tag{9}$$

The vertex method is an effective and simple method to calculate the distance between two triangular fuzzy numbers. According to the vertex method, two triangular fuzzy numbers $\tilde{a}$ and $\tilde{b}$ are identical if and only if $d_v(\tilde{a}, \tilde{b}) = 0$ (Chen, 2000).

Let the fuzzy rating and importance weight of the kth decision maker be $\tilde{x}_{ijk} = (a_{ijk}, b_{ijk}, c_{ijk})$ and $\tilde{w}_{ijk} = (w_{jk1}, w_{jk2}, w_{jk3})$; $\{i = 1,2,\ldots,m,\ j = 1,2,\ldots,n\}$, respectively.

Hence, the aggregated fuzzy ratings $(\tilde{x}_{ij})$ of alternatives with respect to each criterion can be calculated as

$$\tilde{x}_{ij} = (a_{ij}, b_{ij}, c_{ij}) \quad \text{where } a_{ij} = \min_k\{a_{ijk}\},$$
$$b_{ij} = \frac{1}{K}\sum_{k=1}^{K} b_{ijk},\ c_{ij} = \max_k\{c_{ijk}\}. \tag{10}$$

The problem can be described by following sets:

(i) a set of J possible candidates called $A = \{A_1, A_2, \ldots, A_j\}$;
(ii) a set of n criteria, $C = \{C_1, C_2, \ldots, C_i\}$;
(iii) a set of performance ratings of A_j $(j = 1,2,3,\ldots,J)$ with respect to criteria C_i $(i = 1,2,3,\ldots,n)$ called $\widetilde{X} = \{\tilde{x}_{ij},\ i = 1,2,3,\ldots,n,\ j = 1,2,3,\ldots,J\}$;
(iv) a set of importance weights of each criterion w_i $(i = 1,2,3,\ldots,n)$.

As stated above, a personnel-selection problem can be concisely expressed in matrix format as follows:

$$\widetilde{X} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ \tilde{x}_{j1} & \tilde{x}_{j2} & \cdots & \tilde{x}_{jn} \end{bmatrix}.$$

Definition 2. The weighted normalized fuzzy-decision matrix can be represented as

$$\widetilde{V} = [\tilde{v}_{ij}]_{nxJ} \quad \{i = 1,2,\ldots,n,\ j = 1,2,\ldots,J\} \quad \text{where } \tilde{v}_{ij} = \tilde{r}_{ij}(\cdot)w_i. \tag{11}$$

Fuzzy TOPSIS steps can be outlined as follows (Onut et al., 2009):

Step 1: Choose the linguistic ratings $(\tilde{x}_{ij},\ i = 1,2,3,\ldots n,\ j = 1,2,3,\ldots,J)$ for alternatives with respect to criteria.
To avoid complexity of mathematical operations in a decision process, the linear scale transformation is used here to transform the various criteria scales into comparable scales. The set of criteria can be divided into benefit criteria (the larger the rating, the greater the preference) and cost criteria (the smaller the rating, the greater the preference). Let $\tilde{x}_{ij} = (a_{ij}, b_{ij}, c_{ij})$, $\tilde{x}_j^- = (a_j^-, b_j^-, c_j^-)$ and $\tilde{x}_j^* = \left(a_j^*, b_j^*, c_j^*\right)$. Get B and C are the sets of benefit criteria and cost criteria, respectively, we have

$$\tilde{r}_{ij} = \tilde{x}_{ij}/\tilde{x}_j^* = \left(\frac{a_{ij}}{a_j^*}, \frac{b_{ij}}{b_j^*}, \frac{c_{ij}}{c_j^*}\right), \quad j \in B,$$
$$\tilde{r}_{ij} = \tilde{x}_j^-/\tilde{x}_{ij} = \left(\frac{a_j^-}{a_{ij}}, \frac{b_j^-}{b_{ij}}, \frac{c_j^-}{c_{ij}}\right), \quad j \in C, \tag{12}$$

Step 2: The normalization method mentioned above is designed to preserve the property in which the elements $\tilde{r}_{ij}$, $\forall i,j$ are standardized (normalized) triangular fuzzy numbers. Considering the different importance of each criterion, the weighted normalized fuzzy-decision matrix is constructed as

$$\widetilde{V} = [\tilde{v}_{ij}]_{nxJ} \quad \{i = 1,2,\ldots,n,\ j = 1,2,\ldots,J\}$$
$$\text{where } \tilde{v}_{ij} = \tilde{r}_{ij}(\cdot)w_i. \tag{13}$$

Step 3: According to the weighted normalized fuzzy decision matrix, normalized positive triangular fuzzy numbers can also approximate the elements $\tilde{v}_{ij}$, $\forall i,j$. Then, the fuzzy positive-ideal solution (FPIS,A^*) and fuzzy negative-ideal solution (FNIS,A^-) can be defined as

$$A^* = \{\tilde{v}_1^*, \ldots, \tilde{v}_i^*\} = \{\max_j v_{ij} I\, i \in I\} \quad \{i = 1,2,\ldots,n,\ j = 1,2,\ldots,J\}, \tag{14}$$
$$A^- = \{\tilde{v}_1^-, \ldots, \tilde{v}_i^-\} = \{\min_j v_{ij} I i \in I\} \quad \{i = 1,2,\ldots,n,\ j = 1,2,\ldots,J\}, \tag{15}$$

where I is criteria.

Step 4: The distance of each alternative from A^* and A^- can be currently calculated as

$$D_j^* = \sum_{j=1}^{n} d\left(\tilde{v}_{ij}, \tilde{v}_j^*\right) \quad \{j = 1,2,\ldots,J\}, \tag{16}$$
$$D_j^- = \sum_{j=1}^{n} d\left(\tilde{v}_{ij}, \tilde{v}_j^-\right) \quad \{j = 1,2,\ldots,J\}, \tag{17}$$

where D is the distance measurement between two fuzzy numbers.

Step 5: A closeness coefficient is defined to determine the ranking order of all possible alternatives once D_j^* and D_j^- of each alternative A_j $(j = 1,2,\ldots,J)$ has been calculated. The closeness coefficient represents the distances to the fuzzy positive-ideal solution (A^*) and the fuzzy negative-ideal solution (A^-) simultaneously by taking the relative closeness to the fuzzy positive-ideal solution. The closeness coefficient (CC_j) of each alternative is calculated as

$$CC_j = \frac{D_j^-}{D_j^- + D_j^*}, \quad \{j = 1,2,\ldots,J\}. \tag{18}$$

It is clear that $CC_j = 1$ if $A_j = A^*$ and $CC_j = 0$ if $A_j = A^-$. In other words, alternative A_j is closer to the FPIS (A^*) and farther from FNIS (A^-) as CC_i approaches to 1. According to the descending order of CC_j, we can determine the ranking order of all alternatives and select the best one from among a set of feasible alternatives.

5. Fuzzy ELECTRE

The ELECTRE (ELimination Et Choix Traduisant la REalité) method originated from Roy in the late 1960s. The ELECTRE method is based on the study of outranking relations and uses concordance and discordance indexes to analyze the outranking relations among the alternatives. Concordance and discordance indexes can be viewed as measurements of satisfaction and dissatisfaction that a decision-maker chooses one alternative over the other.

Suppose a MCDM problem has m alternatives $(A_1, A_2, \ldots, A_m)$ and n decision criteria/attributes $(C_1, C_2, \ldots, C_n)$. Each alternative is evaluated with respect to the n criteria/attributes. All the values/ratings assigned to the alternatives with respect to each criterion form a decision matrix denoted by $X = (x_{ij})_{m\times n}$. Let $W = (w_1, w_2, \ldots, w_n)$ be the relative weight vector about the criteria, satisfying $\sum_{j=1}^{n} w_j = 1$. Then the ELECTRE method can be summarized as follows (Yoon & Hwang, 1995).

- Normalize the decision matrix $X = (x_{ij})_{m\times n}$ by calculating r_{ij}, which represents the normalized criteria/attribute value/rating,

$$r_{ij} = \frac{1/x_{ij}}{\sqrt{\sum_{i=1}^{m} 1/x_{ij}^2}} \text{ for the minimization objective, where}$$
$$i = 1,2,\ldots,m \text{ and } j = 1,2,\ldots,n, \tag{19}$$
$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \text{ for the maximization objective, where}$$
$$i = 1,2,\ldots,m \text{ and } j = 1,2,\ldots,n. \tag{20}$$

- Calculate the weighted normalized decision matrix $V = (v_{ij})_{m\times n}$

$$v_{ij} = r_{ij} \cdot w_j, \text{ where } i = 1,2,\ldots,m \text{ and } j = 1,2,\ldots,n, \tag{21}$$

where w_j is the relative weight of the jth criterion or attribute, and $\sum_{j=1}^{n} w_j = 1$.

- Determine the concordance and discordance sets. For each pair of alternatives A_p and A_q ($p,q = 1,2,\ldots,m$ and $p \neq q$) the set of criteria is divided into two distinct subsets. If alternative A_p is preferred to A_q for all criteria, the concordance set is composed. This can be written as

$$C(p,q) = \{j | \upsilon_{pj} > \upsilon_{qj}\}, \tag{22}$$

where υ_{pj} is the weighted normalized rating of alternative A_p with respect to the jth criterion. In other words, $C(p,q)$ is the collection of attributes where A_p is better than or equal to A_q. The complement of $C(p,q)$, the discordance set, contains all criteria for which A_p is worse than A_q. This can be written as

$$D(p,q) = \{j | \upsilon_{pj} < \upsilon_{qj}\}. \tag{23}$$

- Calculate the concordance and discordance indexes. The concordance index of $C(p,q)$ is defined as

$$C_{pq} = \sum_{j^*} w_{j^*}, \tag{24}$$

where j^* are attributes contained in the concordance set $C(p,q)$. The discordance index $D(p,q)$ represents the degree of disagreement in $A_p \to A_q$ and can be defined as

$$D_{pq} = \frac{\sum_{j+} |\upsilon_{pj^+} - \upsilon_{qj^+}|}{\sum_j |\upsilon_{pj} - \upsilon_{qj}|}, \tag{25}$$

where j^+ are attributes contained in the discordance set $D(p,q)$ and υ_{ij} is the weighted normalized evaluation of alternatives i on criterion j.
- Outranking relationship. The method defines that A_p outranks A_q when $C_{pq} \geqslant \overline{C}$ and $D_{pq} \leqslant \overline{D}$ where $\overline{C}$ and $\overline{D}$ are the averages of C_{pq} and D_{pq}, respectively.

According to Sevkli (2010), the basic steps of the fuzzy ELECTRE method can be described as follows.

Step 1: A panel of decision-makers (DMs) who are knowledgeable concerning the supplier selection process is established. The group has K decision makers (i.e. $D_1, D_2, \ldots, D_k$) who are responsible for the ranking (y_{jk}) of each criterion (i.e. $C_1, C_2, \ldots, C_n$) in increasing order. Then, the aggregated fuzzy importance weight for each criterion can be described as fuzzy triangular numbers $\tilde{w}_j = (a_j, b_j, c_j)$ for $k = 1,2,\ldots,K$ and $j = 1,2,\ldots,n$. The aggregated fuzzy importance weight can be determined as follows:

$$a_j = \min_k \{y_{jk}\}, \quad b_j = \frac{1}{K} \sum_{k=1}^{K} y_{jk}, \quad c_j = \max_k \{y_{jk}\}. \tag{26}$$

Then, the aggregated fuzzy importance weight for each criterion is normalized as follows:

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

where

$$w_{j1} = \frac{1/a_j}{\sum_{j=1}^{n} 1/a_j}, \quad w_{j2} = \frac{1/b_j}{\sum_{j=1}^{n} 1/b_j}, \quad w_{j3} = \frac{1/c_j}{\sum_{j=1}^{n} 1/c_j}. \tag{27}$$

Then the normalized aggregated fuzzy importance weight matrix is constructed as $\widetilde{W} = [\tilde{w}_1, \tilde{w}_2, \ldots, \tilde{w}_n]$.

Step 2: A decision matrix is formed

$$X = \begin{bmatrix} x_{11} & x_{12} & \ldots & x_{1n} \\ x_{21} & x_{22} & \ldots & x_{2n} \\ \ldots & \ldots & \ldots & \ldots \\ x_{m1} & x_{m2} & \ldots & x_{mn} \end{bmatrix}. \tag{28}$$

Step 3: After forming the decision matrix, normalization is applied. The calculation is performed using formulae (1) and (2). Then, the normalized decision matrix is obtained as

$$R = \begin{bmatrix} r_{11} & r_{12} & \ldots & r_{1n} \\ r_{21} & r_{22} & \ldots & r_{2n} \\ \ldots & \ldots & \ldots & \ldots \\ r_{m1} & r_{m2} & \ldots & r_{mn} \end{bmatrix}. \tag{29}$$

Step 4: Considering the different weights of each criterion, the weighted normalized decision matrix is computed by multiplying the importance weight of the evaluation criteria and the values in the normalized decision matrix. The weighted normalized decision matrix $\widetilde{V}$ for each criterion is defined as

$$\widetilde{V} = [\tilde{\upsilon}_{ij}]_{m \times n} \text{ for } i = 1,2,\ldots,m \text{ and } j = 1,2,\ldots,n, \text{ where } \tilde{\upsilon}_{ij} = r_{ij} \times \tilde{w}_j,$$

and

$$V^1 = \begin{bmatrix} \upsilon^1_{11} & \upsilon^1_{12} & \ldots & \upsilon^1_{1n} \\ \upsilon^1_{21} & \upsilon^1_{22} & \ldots & \upsilon^1_{2n} \\ \ldots & \ldots & \ldots & \ldots \\ \upsilon^1_{m1} & \upsilon^1_{m2} & \ldots & \upsilon^1_{mn} \end{bmatrix},$$
$$V^2 = \begin{bmatrix} \upsilon^2_{11} & \upsilon^2_{12} & \ldots & \upsilon^2_{1n} \\ \upsilon^2_{21} & \upsilon^2_{22} & \ldots & \upsilon^2_{2n} \\ \ldots & \ldots & \ldots & \ldots \\ \upsilon^2_{m1} & \upsilon^2_{m2} & \ldots & \upsilon^2_{mn} \end{bmatrix},$$
$$V^3 = \begin{bmatrix} \upsilon^3_{11} & \upsilon^3_{12} & \ldots & \upsilon^3_{1n} \\ \upsilon^3_{21} & \upsilon^3_{22} & \ldots & \upsilon^3_{2n} \\ \ldots & \ldots & \ldots & \ldots \\ \upsilon^3_{m1} & \upsilon^3_{m2} & \ldots & \upsilon^3_{mn} \end{bmatrix}. \tag{30}$$

Here $\tilde{\upsilon}_{ij}$ denote normalized positive triangular fuzzy numbers.

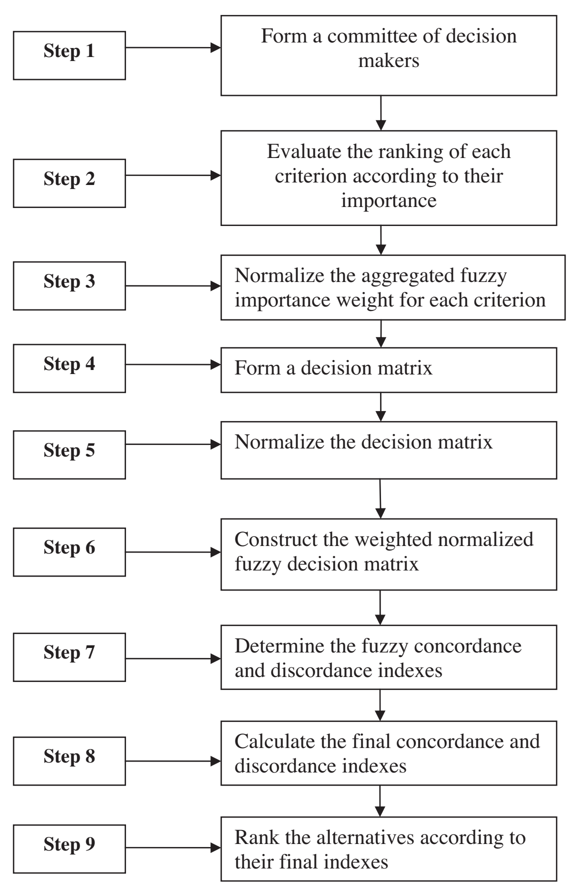

Fig. 2. The steps of the fuzzy ELECTRE method.

Step 5: The concordance and discordance indexes are calculated for different weights of each criterion (w_{j1}, w_{j2}, w_{j3}). The concordance index C_{pq} represents the degree of confidence in pairwise judgments ($A_p \rightarrow A_q$). The concordance index C_{pq} for the proposed model is defined as

$$C_{pq}^1 = \sum_{j*} w_{j1}, \quad C_{pq}^2 = \sum_{j*} w_{j2}, \quad C_{pq}^3 = \sum_{j*} w_{j3}, \tag{31}$$

where j^* are attributes contained in the concordance set $C(p,q)$.

Step 6: The discordance index, on the other hand, measures the power of $D(p,q)$. The discordance index $D(p,q)$, which represents the degree of disagreement in ($A_p \rightarrow A_q$), can be defined as

$$D_{pq}^1 = \frac{\sum_{j^+}\left|v_{pj^+}^1 - v_{qj^+}^1\right|}{\sum_j\left|v_{pj}^1 - v_{qj}^1\right|}, \quad D_{pq}^2 = \frac{\sum_{j^+}\left|v_{pj^+}^2 - v_{qj^+}^2\right|}{\sum_j\left|v_{pj}^2 - v_{qj}^2\right|},$$
$$D_{pq}^3 = \frac{\sum_{j^+}\left|v_{pj^+}^3 - v_{qj^+}^3\right|}{\sum_j\left|v_{pj}^3 - v_{qj}^3\right|}, \tag{32}$$

where j^+ are attributes that are contained in the discordance set $D(p,q)$ and v_{ij} is the weighted normalized evaluation of alternatives i on criterion j.

Step 7: The final concordance and discordance indexes are computed using the following formula:

$$C_{pq}^* = \sqrt[z]{\prod_{z=1}^{Z} C_{pq}^z}, \quad D_{pq}^* = \sqrt[z]{\prod_{z=1}^{Z} D_{pq}^z}, \quad \text{where } Z = 3. \tag{33}$$

This formula can be considered as the defuzzification procedure. The dominance relationship of alternative A_p over alternative A_q becomes stronger with a larger final concordance index C_{pq} and a smaller discordance index D_{pq}. The outranking relation is obtained by applying the following equation procedure to obtain the kernel, which is the subset of the best alternatives:

$$\text{If } C(p,q) \geqslant \overline{C} \text{ and } D(p,q) \leqslant \overline{D}, \tag{34}$$

where $\overline{C}$ and $\overline{D}$ are the averages of C_{pq} and D_{pq}, respectively. The general steps of the fuzzy ELECTRE approach are summarized in Fig. 2.

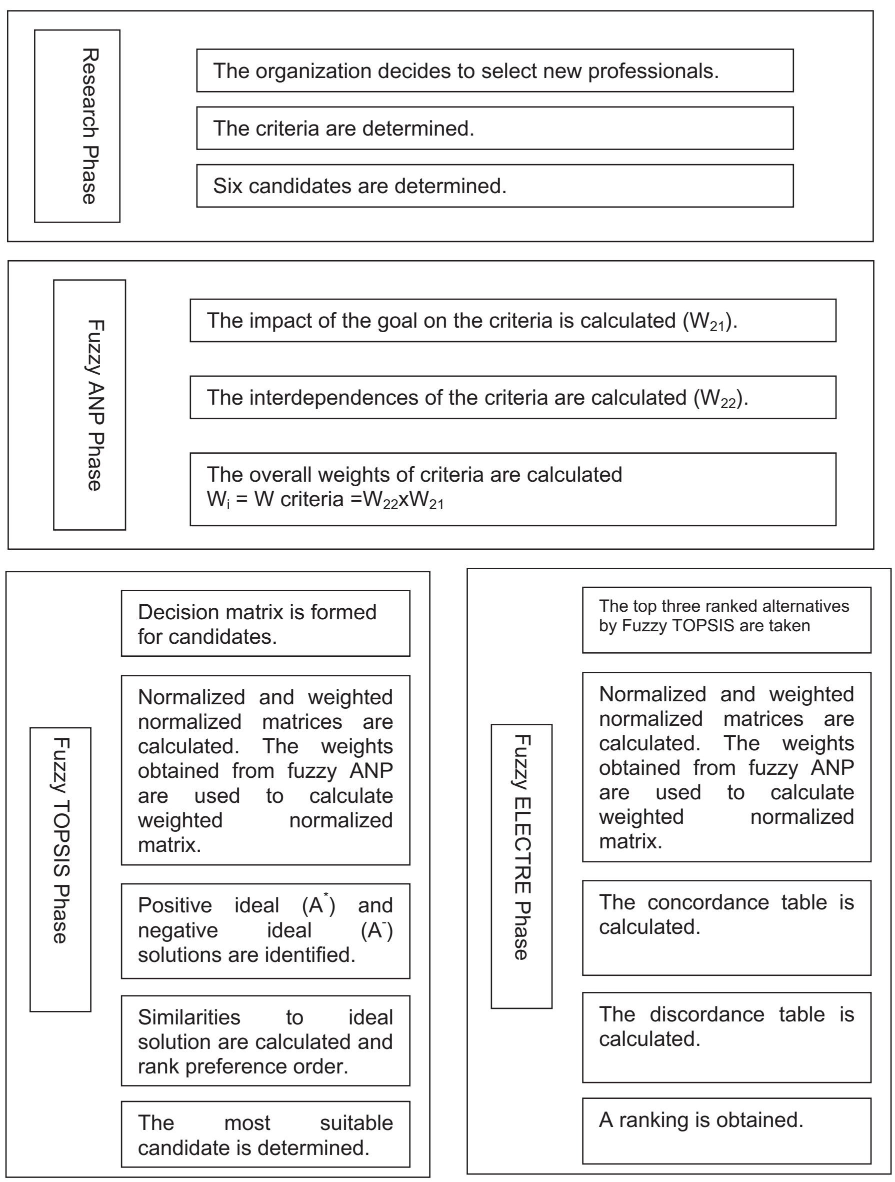

Fig. 3. Proposed model.

Table 3
Criteria for sniper selection.

Physical factors	
C1	Physical strength and stamina
C2	Not being a substance abuser
C3	Good health
Functional factors	
C4	Rapid decision making and analytical thinking ability
C5	Being good at marksmanship
C6	Ability to control body and concentrate
Personality factors	
C7	Emotional stability
C8	Ability to work independently
C9	Patience
C10	Calmness

Table 4
Interdependences between criteria.

Dependent criteria	Depending on
C1	C2, C3, C6, C9
C2	C3, C6, C9
C3	C1, C2, C7
C4	C3, C7, C8
C5	C2, C4, C6
C6	C1, C2, C3, C4, C7, C9
C7	C6, C8, C9, C10
C8	C1, C4, C5, C7
C9	C7, C8, C10
C10	C7, C9

6. Application of the integrated model to the professional selection problem

The proposed model for the professional selection problem, composed of fuzzy ANP, fuzzy TOPSIS and fuzzy ELECTRE methods, consists of four basic stages: (1) identify the criteria to be used in the model, (2) fuzzy ANP computations, (3) evaluation of suitable candidates with fuzzy TOPSIS and (4) determination of the final rank with fuzzy ELECTRE. Schematic diagram of the proposed model for sniper selection is provided in Fig. 3.

The evaluation of snipers' qualifications and a selection model with ANP is developed with the participation of experts. Initially, the qualifications that should have been in a good sniper were established. A number of basic qualifications for every soldier and not distinguishing to marksmanship were excluded from initially established 48 criteria. According to the experts' view, for the evaluation process, it was decided to use 10 criteria for selecting snipers from currently serving professional soldiers, given in Table 3.

The set of physical properties are expressed as the minimum physical properties that snipers need to be able to take part in operations, which are in common with all soldiers. The physical condition criterion is to ensure the physical qualifications at work to be done. Being healthy can be defined as having no chronic health problems. Finally, not being a substance abuser can be considered as the most important physical criterion. Although it has not been fully investigated, it is clear that substance abuse will create a negative impact on marksmanship, which is a very precise occupation, demanding full attention and bodily control.

A set of functional properties are generally expressed as the skills that are related to the snipers' duties and needed during the mission. According to this, controlling the body and concentrating are the ability to focus the target in cases of long term stagnation. Rapid decision making in dynamic situations and the ability to make calculations about position by predicting movement are expressed as sapid decision making and analytical thinking ability. Being a good sniper means, if possible, to hit with the first shot.

A set of personal properties express the characteristics which are taken into account for general intake into the military units, but are directly relevant to marksmanship. To keep his mind away from problems which is necessary in order to ensure the fire accuracy of sniper can be expressed as focusing the work through distinguishing the work and problems psychologically. Patience and calmness, due to the nature of the job, is thought to be important for the sniper in terms of waiting targets and timing accuracy. Finally, flexible thinking, and not being independent and prescriptive will be an important characteristic for sniper in adaptation to dynamic situations.

The dependence between the criteria according to the group decision is stated in Table 4.

Table 5
Pair-wise comparison for W_{21}.

	C1			C2			C3			C4			C5			C6		
	l	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*
C1	1	1	1	4	5	6	0.25	0.33	0.5	8	9	10	8	9	10	8	9	10
C2	0.17	0.2	0.25	1	1	1	0.13	0.14	0.17	2	3	4	6	7	8	0.25	0.33	0.5
C3	2	3	4	6	7	8	1	1	1	8	9	10	8	9	10	8	9	10
C4	0.1	0.11	0.13	0.25	0.33	0.5	0.1	0.11	0.13	1	1	1	2	3	4	0.25	0.33	0.5
C5	0.1	0.11	0.13	0.13	0.14	0.17	0.1	0.11	0.13	0.25	0.33	0.5	1	1	1	0.13	0.14	0.17
C6	0.1	0.11	0.13	2	3	4	0.1	0.11	0.13	2	3	4	6	7	8	1	1	1
C7	2	3	4	0.1	0.11	0.13	1	1	1	8	9	10	8	9	10	8	9	10
C8	0.13	0.14	0.17	0.25	0.33	0.5	0.1	0.11	0.13	1	1	1	4	5	6	1	1	1
C9	1	1	1	0.13	0.14	0.17	1	1	1	8	9	10	8	9	10	8	9	10
C10	1	1	1	0.13	0.14	0.17	0.25	0.33	0.5	8	9	10	8	9	10	6	7	8

	C7			C8			C9			C10			Geometric average			Fuzzy weight W_{21}		
	l	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*
C1	0.25	0.33	0.5	6	7	8	1	1	1	1	1	1	1.94	2.21	2.56	0.13	0.15	0.17
C2	8	9	10	2	3	4	6	7	8	6	7	8	1.43	1.75	2.1	0.1	0.12	0.14
C3	1	1	1	8	9	10	1	1	1	2	3	4	3.16	3.64	4.08	0.21	0.24	0.27
C4	0.1	0.11	0.13	1	1	1	0.1	0.11	0.13	0.1	0.11	0.13	0.26	0.3	0.35	0.02	0.02	0.02
C5	0.1	0.11	0.13	0.17	0.2	0.25	0.1	0.11	0.13	0.1	0.11	0.13	0.15	0.17	0.2	0.01	0.01	0.01
C6	0.1	0.11	0.13	1	1	1	0.1	0.11	0.13	0.13	0.14	0.17	0.44	0.52	0.59	0.03	0.03	0.04
C7	1	1	1	8	9	10	1	1	1	2	3	4	2.1	2.41	2.69	0.14	0.16	0.18
C8	0.1	0.11	0.13	1	1	1	0.1	0.11	0.13	0.1	0.11	0.13	0.32	0.36	0.41	0.02	0.02	0.03
C9	1	1	1	8	9	10	1	1	1	2	3	4	2	2.21	2.41	0.13	0.15	0.16
C10	0.25	0.33	0.5	8	9	10	0.25	0.33	0.5	1	1	1	1.2	1.39	1.67	0.08	0.09	0.11

All these criteria are benefit criteria. All the calculations were carried out using Ms. Excel. In the first phase of the study, the relative fuzzy importance degrees of the individual criteria using triangular fuzzy numbers are determined, and then triangular fuzzy importance weights are derived from the fuzzy pair-wise comparison matrices (i.e., calculate W_{21}) using the logarithmic least squares method (Eq. (8)). Table 5 summarizes pair-wise comparison for W_{21}.

The fuzzy interdependences among the criteria (the feedback of the criteria) are subsequently specified based on the linguistic evaluation. By using the logarithmic least squares method (Eq. (8)) again, triangular fuzzy importance weights are derived and these weights are arranged into the fuzzy interdependence matrix (i.e., calculate W_{22}). The data for the fuzzy feedbacks among the criteria is composed of the six pair-wise comparison matrices for each criterion. The interdependences for criterion C1 is shown in Table 6 as an example.

Hence the fuzzy weights of the evaluation criteria are determined (i.e., $w_i = w_{\text{criteria}} = W_{22} \times W_{21}$). Tables 7 and 8 summarize W_{22}, W_{21} and w_i, respectively.

This phase is known essentially as the FANP phase essentially. The second phase of the study, which is called the fuzzy TOPSIS phase, starts establishing fuzzy evaluations of the alternative suppliers ($A1, A2, \ldots, A6$) with respect to the individual criteria by using triangular fuzzy numbers again. This is a decision matrix for ranking alternatives and indicates the performance ratings of the alternatives according to the criteria. After constructing the decision matrix, a normalized decision matrix is calculated. Decision matrix is shown in Table 9.

Table 8
Values of W_{21} and W_i.

	W_{21}			W_i		
C1	0.13	0.15	0.17	0.13	0.18	0.24
C2	0.1	0.12	0.14	0.11	0.16	0.22
C3	0.21	0.24	0.27	0.09	0.13	0.19
C4	0.02	0.02	0.02	0.01	0.01	0.02
C5	0.01	0.01	0.01	0	0	0
C6	0.03	0.03	0.04	0.1	0.14	0.19
C7	0.14	0.16	0.18	0.14	0.2	0.26
C8	0.02	0.02	0.03	0.06	0.09	0.12
C9	0.13	0.15	0.16	0.05	0.06	0.09
C10	0.08	0.09	0.11	0.02	0.02	0.03

Then the weighted normalized fuzzy decision matrix is calculated. Weights which are used to calculate weighted normalized fuzzy decision matrix are derived from the FANP. The weighted normalized value $\tilde{v}_{ii}$ calculated by using Eq. (11). Table 10 is the weighted normalized decision matrix.

Moreover positive-ideal (A^*) and negative-ideal (A^-) solutions are identified. The fuzzy positive-ideal solution (FPIS, A^*) and the fuzzy negative-ideal solution (FNIS, A^-) are calculated using Eqs. (14) and (15). The distance of each alternative from A^* and A^- is computed by using Eqs. (16) and (17). Fuzzy preferences are normalized positive triangular fuzzy numbers, so we can define the fuzzy positive-ideal solution (FPIS, A^*) and the fuzzy negative-ideal solution (FNIS, A^-). In the final step, similarities to the ideal solution are calculated and ranked in preference orders. Then, an alternative with maximum CC_j^* is chose or alternatives according to CC_j^* are ranked in descending order. Table 11 summarizes the

Table 6
Interdependences for C1.

	C2			C3			C6			C9			Geometric average			Fuzzy weight W_{22}		
	l	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*
C2	1	1	1	2	3	4	4	5	6	6	7	8	2.63	3.2	3.72	0.45	0.55	0.64
C3	0.25	0.33	0.5	1	1	1	2	3	4	6	7	8	1.32	1.63	2	0.23	0.28	0.34
C6	0.17	0.2	0.25	0.25	0.33	0.5	1	1	1	4	5	6	0.64	0.76	0.93	0.11	0.13	0.16
C9	0.13	0.14	0.17	0.13	0.14	0.17	0.17	0.2	0.25	1	1	1	0.23	0.25	0.29	0.04	0.04	0.05

Table 7
Pair-wise comparison for values of W_{22}.

	C1			C2			C3			C4			C5		
	l	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*
C1	0	0	0	0	0	0	0.52	0.64	0.75	0	0	0	0	0	0
C2	0.45	0.55	0.64	0	0	0	0.21	0.26	0.33	0	0	0	0.52	0.64	0.75
C3	0.23	0.28	0.34	0.52	0.64	0.75	0	0	0	0.52	0.64	0.75	0	0	0
C4	0	0	0	0	0	0	0	0	0	0	0	0	0.21	0.26	0.33
C5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C6	0.11	0.13	0.16	0.21	0.26	0.33	0	0	0	0	0	0	0.09	0.1	0.13
C7	0	0	0	0	0	0	0.09	0.1	0.13	0.21	0.26	0.33	0	0	0
C8	0	0	0	0	0	0	0	0	0	0.09	0.1	0.13	0	0	0
C9	0.04	0.04	0.05	0.09	0.1	0.13	0	0	0	0	0	0	0	0	0
C10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

	C6			C7			C8			C9			C10		
	l	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*
C1	0.35	0.42	0.48	0	0	0	0.45	0.55	0.64	0	0	0	0	0	0
C2	0.25	0.29	0.34	0	0	0	0	0	0	0	0	0	0	0	0
C3	0.15	0.17	0.19	0	0	0	0	0	0	0	0	0	0	0	0
C4	0.06	0.07	0.08	0	0	0	0.23	0.28	0.34	0	0	0	0	0	0
C5	0	0	0	0	0	0	0.11	0.13	0.16	0	0	0	0	0	0
C6	0	0	0	0.45	0.55	0.64	0	0	0	0	0	0	0	0	0
C7	0.03	0.03	0.04	0	0	0	0.04	0.04	0.05	0.52	0.64	0.75	0.61	0.75	0.87
C8	0.03	0.03	0.04	0.23	0.28	0.34	0	0	0	0.21	0.26	0.33	0	0	0
C9	0.02	0.02	0.02	0.11	0.13	0.16	0	0	0	0	0	0	0.22	0.25	0.31
C10	0	0	0	0.04	0.04	0.05	0	0	0	0.09	0.1	0.13	0	0	0

Table 9
Decision matrix for alternatives.

	A1			A2			A3			A4			A5			A6		
C1	1	1	1	6	7	8	1	1	1	6	7	8	4	5	6	2	3	4
C2	4	5	6	2	3	4	4	5	6	4	5	6	8	9	10	1	1	1
C3	6	7	8	4	5	6	1	1	1	2	3	4	4	5	6	6	7	8
C4	1	1	1	4	5	6	4	5	6	2	3	4	8	9	10	4	5	6
C5	4	4	4	6	6	6	5	5	5	8	8	8	6	6	6	9	9	9
C6	2	3	4	1	1	1	4	5	6	6	7	8	2	3	4	2	3	4
C7	4	5	6	4	5	6	2	3	4	1	1	1	6	7	8	6	7	8
C8	2	3	4	1	1	1	4	5	6	2	3	4	6	7	8	2	3	4
C9	8	9	10	2	3	4	8	9	10	8	9	10	2	3	4	8	9	10
C10	1	1	1	2	3	4	1	1	1	8	9	10	1	1	1	4	5	6

Table 10
The weighted normalized decision matrix.

	A1			A2			A3			A4			A5			A6		
C1	0.02	0.03	0.03	0.13	0.18	0.24	0.02	0.03	0.03	0.13	0.18	0.24	0.09	0.13	0.18	0.04	0.08	0.12
C2	0.06	0.09	0.13	0.03	0.05	0.09	0.06	0.09	0.13	0.06	0.09	0.13	0.11	0.16	0.22	0.01	0.02	0.02
C3	0.09	0.13	0.19	0.06	0.1	0.14	0.02	0.02	0.02	0.03	0.06	0.09	0.06	0.1	0.14	0.09	0.13	0.19
C4	0	0	0	0	0.01	0.01	0	0.01	0.01	0	0	0.01	0.01	0.01	0.02	0	0.01	0.01
C5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C6	0.03	0.06	0.09	0.02	0.02	0.02	0.07	0.1	0.14	0.1	0.14	0.19	0.03	0.06	0.09	0.03	0.06	0.09
C7	0.09	0.14	0.2	0.09	0.14	0.2	0.05	0.08	0.13	0.02	0.03	0.03	0.14	0.2	0.26	0.14	0.2	0.26
C8	0.02	0.04	0.06	0.01	0.01	0.01	0.04	0.06	0.09	0.02	0.04	0.06	0.06	0.09	0.12	0.02	0.04	0.06
C9	0.05	0.06	0.09	0.01	0.02	0.04	0.05	0.06	0.09	0.05	0.06	0.09	0.01	0.02	0.04	0.05	0.06	0.09
C10	0	0	0	0	0.01	0.01	0	0	0	0.02	0.02	0.03	0	0	0	0.01	0.01	0.02

Table 11
The results.

	D_j^+	D_j^-	CC_j	Order
A1	0.82	0.49	0.37	4
A2	0.84	0.47	0.36	5
A3	0.91	0.38	0.3	6
A4	**0.76**	**0.56**	**0.42**	**2**
A5	**0.63**	**0.71**	**0.53**	**1**
A6	**0.78**	**0.55**	**0.41**	**3**

results. Eq. (18) is used to calculate distances to ideal solutions. According to the last step, the best alternative for the supplier selection problem is determined as A5.

The top three ranked alternatives by Fuzzy TOPSIS, A5, A4 and A6, are bold in Table 11 and taken into the analysis. The corresponding values of the decision matrix shown in Table 9 are used for three alternatives. Then the normalized decision matrix is calculated by Eq. (29). Afterwards, the weighted normalized decision matrix is formed by Eq. (30). The required weights of the criteria are the values found in the Fuzzy ANP.

The concordance and discordance values of the alternatives are calculated by Eqs. (31) and (32), respectively, as shown in Tables 12 and 13. The fuzzy concordance and discordance numbers are defuzzified by Eq. (33) and listed in the last column of Tables 12 and 13.

The final ranking is obtained by Fuzzy ELECTRE Eq. (34) and it is shown in Table 14.

Table 12
Concordance values.

	Fuzzy value			Defuzzified value
A4–A5	0.264	0.262	0.265	0.263
A4–A6	0.206	0.200	0.199	0.202
A5–A4	0.726	0.728	0.725	0.726
A5–A6	0.084	0.081	0.080	0.081
A6–A4	0.653	0.658	0.655	0.655
A6–A5	0.123	0.124	0.128	0.125

Table 13
Discordance values.

	Fuzzy value			Defuzzified value
A4–A5	0.314	0.337	0.343	0.331
A4–A6	0.323	0.379	0.421	0.372
A5–A4	0.071	−0.022	−0.093	0.052
A5–A6	0.233	0.274	0.307	0.270
A6–A4	0.414	0.351	0.301	0.352
A6–A5	0.004	−0.006	−0.017	0.007

Table 14
Final ranking.

Rank	Alternative
1	A5
2	A6
3	A4

7. Conclusion

A model composed of combining three different MCDM techniques is proposed for sniper selection as a part of personnel selection. Fuzzy logic is applied to all techniques in order to make the evaluation process more precise and more flexible for the decision makers. The usage of the fuzzy sets in describing uncertainties in different factors simplifies the complex structure of the decision phase. In other words, using linguistic preferences can be very useful for uncertain situations. The proposed fuzzy hybrid multicriteria decision making model combines Fuzzy ANP, Fuzzy TOPSIS, and Fuzzy ELECTRE. The model provides the use of both qualitative and quantitative factors. As mentioned before the proposed hybrid structure of three MCDM techniques and proposing a MCDM approach for sniper real selection case are the unique features of the study, which has hitherto not been reported in the literature. The initial criteria evaluation may also be used for future studies as reference. Various different kinds of MCDM methods can be hired in future studies regarding personnel selection.

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