

MACHINE MAINTENANCE MANAGER SELECTION PROCESS WITH FUZZY TOPSIS TECHNIQUE: AN EMPIRICAL APPLICATION

Burcu DOĞANALP*

ABSTRACT

Because of the fact that today human resources has been accepted as one of the most important source of competitive advantage of an organization, finding the right person for the job has become as a vital human resource management function. In this context, determining the approach to be used in the selection process is prerequisite. As a result of that the decision makers use linguistic variables while evaluating multiple criteria and candidates, human resource selection process based on the qualitative more than quantitative data brings vagueness and fuzziness. This paper presents fuzzy TOPSIS method being used while group decision making in the fuzzy environment and displays the method's process with an application. For this purpose, as decision makers, three top managers in a business organization that is in the list of "First 500 Big Industrial Organizations of Turkey" evaluated decision criteria and the candidates by using linguistic variables for the positions of machine maintenance manager. These verbal data were transformed into triangular fuzzy numbers for fuzzy TOPSIS method. According to fuzzy TOPSIS, the candidates were ranked from the best to the worst with respect to the calculated closeness coefficients. This study shows that for deciding more accurately and effectively in the human resource selection process, fuzzy TOPSIS model is considerably suitable as an approach of fuzzy multi-criteria decision making.

* Arş. Gör. Dr., Selçuk Üniversitesi

1. INTRODUCTION

In global competition for gaining sustainable competitive advantage human capital is seen as the most important source by the managers. In this context, getting the workforce needed in quantity and quality emerges as an important human resource management function and decision making process. It is suitable to use fuzzy logic approach interpreting uncertain and vague data, inferring from these and modeling fuzziness in the human decision making process for eliminating both uncertainty of this process being derived from verbal data and the subjectivity arising from the process's being based on decision maker's intuition. At the same time, human resource selection is generally a multi-criteria decision making process in which there is group decision. Multi-criteria decision making approach is based on the problem in which there is a choice among the alternatives more than one with respect to the decision criteria.

In the literature, AHP (Analytic Hierarchy Process), ANP (Analytic Network Process), and TOPSIS (Technique for Order Preference by Similarity to Ideal Solutions) methods are widely used as multi-criteria decision making techniques. ELECTRE and PROMETHEE methods are preferred as well but they are not as widely used as them. In addition, it can be seen from the literature that fuzzy AHP, fuzzy ANP, fuzzy TOPSIS methods are widely used in the studies as the hybrid forms of fuzzy logic and AHP, ANP, and TOPSIS. Because of that multi-criteria decision making approaches are based on qualitative data more than quantitative and include personal opinions, in recent years, fuzzy logic approach more suitable when analyzing these data has mostly begun to be preferred.

In this paper, fuzzy TOPSIS method as a fuzzy multi-criteria decision making approach is used for human resource selection process in which there is an evaluation with respect to various criteria and finally group decision is made. The study presents an application of a business organization's interview process conducted for machine maintenance manager position.

2. HUMAN RESOURCE SELECTION PROCESS WITH FUZZY LOGIC TECHNIQUE

Because of that human resources are one of the core competences for an organization to gain and enhance competitive advantage in a knowledge economy (Lin, 2010: 937) today, the enterprises compete with each other for talent. In this context, finding the right person for the vacant job has become one of the most important and indispensable activities (Chen, 2009: 113). Among the functions of human resource management, human resource selection significantly affects the quality of employees and administration, and hence it has attracted intensive attention and is an important topic for the organizations (Lin, 2010: 937). Increasing competition in global markets urges organizations to put more emphasis on human resource selection process (Dursun & Karsak, 2010: 4324). The growing importance of human resource selection process in addition to that it is a very expensive and time taking up activity makes the approach designing to be used in this process prerequisite for the organizations (Chen, 2009:113) and has bought about analytical decision making approaches (Dursun & Karsak, 2010: 4324).

Many scholars have dealt with the human resource selection problem from the decision science point of view. Tools and techniques from operational research and artificial intelligence fields such as fuzzy sets and numbers, expert systems, artificial neural networks and multi-criteria decision analysis techniques have been used to cope with this specific decision problem (Kelemenis et al., 2011: 2775). Multi-criteria decision making approach is interested in the problem which more than one criterion are taken account, more than one alternative are ranked according to these criteria and finally one alternative is chosen among them. Owing to the fact that multi-criteria decision making approaches are based on qualitative more than quantitative information and personal ideas, in recent years fuzzy logic approach being more appropriate for analyzing these information has mostly been preferred (Erginel et al., 2010: 82). Recent studies on the human resource selection problem are listed in Table 1.

Table 1. Recent Studies on the Human Resource Selection Problem

Proposed by	Fuzziness	Techniques	Empirical Application	Group Decision Making
Liang ve Wang (1992)	Yes	Fuzzy Numbers	No	Yes
Carlsson vd. (1997)	No	OWA Operators	Doctoral Student Selection	Yes
Storey Hooper vd. (1998)	No	Expert Systems	Field Grade Officer Selection for Advanced Training	No
McIntyre vd. (1999)	No	Analytic Hierarchy Process	Selection of Division Director in a University Department	No
Chen (2000)	Yes	Fuzzy TOPSIS	No	Yes
Karsak (2000)	Yes	Fuzzy Multiple Objective Programming	No	No
Butkiewicz (2002)	Yes	Fuzzy Numbers	No	No
Cho ve Ngai (2003)	No	Discriminant Analysis, Decision Trees, Artificial Neural Networks	Insurance Sales Agents Selection	No
Yeh (2003)	No	Total Sum Method, Simple Additive Weighting Method, Weighted Product Method, TOPSIS	Scholarship Student Selection	No
Drigas vd. (2004)	Yes	Expert Systems, Neuro-Fuzzy Techniques	Unemployed Matching	No
Huang vd. (2004)	Yes	Fuzzy Neural Networks, Fuzzy Analytic Hierarchy Process, Simple Additive Weighting Method	Middle Manager Selection	Yes
Chen ve Cheng (2005)	Yes	Fuzzy Numbers	No	Yes
Jereb vd. (2005)	No	Expert Systems, Decision Rules	No	No
Saghafian ve Hejazi (2005)	Yes	Fuzzy TOPSIS	No	Yes
Seol ve Sarkis (2005)	No	Analytic Hierarchy Process	No	No

Shih vd. (2005)	No	Nominal Group Technique, Analytic Hierarchy Process, TOPSIS, Borda's Function	On-Line Manager Recruitment	Yes
Baykasoglu vd. (2007)	Yes	Fuzzy Multiple Objective Mathematical Programming, Simulated Annealing	No	No
Golec ve Kahya (2007)	Yes	Fuzzy Numbers, Fuzzy Rules	No	No
Mehrabad ve Brojeny (2007)	No	Expert Systems	Intelligent Selection in an R&D Organization	No
Shih vd. (2007)	No	Group TOPSIS	No	Yes
Chien ve Chen (2008)	No	Decision Trees, Decision Rules	Engineers and Managers Selection in a Semiconductor Company	No
Dağdeviren (2008)	Yes	Analytic Network Process, TOPSIS	Electronics Engineer Selection in a Manufacturing Company	No
Mahdavi vd. (2008)	Yes	Fuzzy TOPSIS	No	Yes
Güngör vd. (2009)	Yes	Fuzzy Analytic Hierarchy Process	No	No
Saremi vd. (2009)	Yes	Fuzzy TOPSIS	Total Quality Management Consultant Selection	Yes

Source: Kelemenis et al., 2011: 2776-2777.

Among the parameters causing the human resource selection activity be described as a decision problem, that it's an uncertain group decision making process, and contains information which is vague and fuzzy are given importance (Kelemenis et al., 2011: 2775). It is clear that decision makers in charge of determining the most appropriate job candidate for the vacant position prefer to use natural language (Ramadan, 2009: 54). Because of expressing verbal information, using natural language causes vague information (Zadeh, 1975: 199). Decision making can be based on decision maker's imprecise perception relying on his/her subjective ideas, experience and beliefs (Saaty & Vargas, 2006: 2). This situation can be considered also for human resource selection as a decision making

process. It is common sense that personnel selectors tend to include as many elements as possible in their decision making process, without being able to clearly define which element has the greatest impact on the outcome of a decision (Petrovic-Lazarevic, 2001: 90). Decision made under these circumstances is defined as subjective judgment (Ayub et al., 2009: 373).

Many real-world problems including human resource selection have been solved with the fuzzy logic in recent years (Golec & Kahya, 2007: 145). In a vague condition, fuzzy logic approach can provide an attractive connection to represent uncertain information and can aggregate them properly (Chang et al., 2006: 543). Since the fuzzy logic approach provides a simultaneous solution to a complex system of competing objectives, it seems to be a proper tool for an organization's staff allocation problem. (Kwak, 2010). Fuzzy set theory can be applied to other business problems whenever there is a need to do modeling with imprecise reasoning processes or ambiguity in human decision making. (Kwak et al., 2003: 279). In this context, fuzzy logic theory appears as an effective tool to incorporate imprecise judgments inherent in the human resource selection process (Karsak, 2001: 393). Because of that it contains multi-criteria; the human resource selection problem is very complex. The human resource selection problem generally concerns with important and complex issues such as (Lin, 2010: 937): (a) How to properly set the importance weights of criteria to reflect the situations in which not all personnel attributes/characteristics are equally important? (b) How to use linguistic and/or numerical scales to evaluate the applicants under multiple criteria? (c) How to aggregate the evaluation results and then rank the applicants?

Multi-criteria decision making methods and fuzzy logic ideally cope with it, given that they incorporate many criteria at the same time, each of them assigned to different importance level. Also, fuzzy logic has the potential to reflect at a very satisfactory degree the vague – most of the times – preferences of the decision maker (Kelemenis et al., 2011: 2774).

Some of the empirical studies on the human resource selection problem of which has taken fuzziness into consideration are:

- The model of Petrovic-Lazarevic (2001) constructed for the selection problem of senior analyst of economy and finance consists of analytic hierarchy process of three levels.
- Kankılıç (2005) has used fuzzy rating method together with pairwise comparison technique based on analytic hierarchy process for the selection of plant manager and production operator.
- Baran and Kılağız (2006) has developed a multi-criteria academician selection system using fuzzy rating and fuzzy ranking.
- While Dağdeviren (2007) has applied analytic hierarchy process method to determine which personnel is going to be promoted in a business; Ecer (2007) has preferred to use fuzzy TOPSIS method in his doctorate thesis for the selection of sales person to serve in a shopping mall.
- Ayub and the others (2009) have applied fuzzy analytic network process to select the post lecturer of a university.
- Liao and Chang (2009) have described the use of analytic network process in the Taiwanese hospital public relations personnel selection process.
- Polychroniou and Giannikos (2009) have used fuzzy TOPSIS method for selection of human resources in a Greek bank.
- Ramadan (2009) has used fuzzy numbers together with memetic algorithm for the selection problem of for personnel as human resource specialist, purchasing specialist, inventory specialist and spare parts seller.
- Lin (2010) has developed a decision support tool by using analytic network process with fuzzy data envelopment for the problem of selecting personnel in an electric and machinery company in Taiwan.

3. METHOD: TOPSIS (TECHNIQUE FOR ORDER PERFORMANCE BY SIMILARITY TO IDEAL SOLUTION) AND FUZZY TOPSIS METHOD

TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method proposed by Hwang and Yoon (1981) has been widely used in the literature to solve multi-criteria decision making problems and bases on choosing the alternative that has the shortest distance from the positive ideal solution (PIS) and the farthest from the negative ideal solution (NIS) (Chen, 2000: 2). So, TOPSIS method accepts the best alternative as closest to the positive ideal solution and farthest from the negative ideal solution. The solution maximizing the benefit criteria and minimizing the cost criteria is called as positive ideal solution; on the contrary, the negative ideal solution maximizes the cost criteria and minimizes the benefit criteria (Wang & Elhag, 2006: 310).

TOPSIS method is composed of the following steps respectively: constructing normalized decision matrix and then weighted normalized decision matrix, determining positive and negative ideal solutions, calculating the Euclidean distance of the alternatives from the positive and negative ideal solutions with respect to all the decision criteria, calculating the closeness coefficients of the alternatives and ranking them with respect to their coefficients.

Because of the fact that human considerations and judgments are often vague and human process of thought is not adaptable to be expressed in exact numerical values the crisp value is inadequate to model real-life situations. So a more realistic approach may be to use linguistic variables instead of numerical values while rating each alternative and assessing weight of the criteria in the problem. In fuzzy TOPSIS method the rating of each alternative and the weight of each criterion are stated as linguistic terms which can be expressed in triangular fuzzy numbers (Chen, 2000: 2). In this context, fuzzy TOPSIS method acquires a different character from TOPSIS method in terms of using linguistic variables instead of exact numerical values.

The Algorithm of Fuzzy TOPSIS Method

In this study we used the algorithm developed by Chen (2000).

Step 1: In a group composed of K decision makers where \tilde{x}_{ij}^K demonstrates the criteria value of i . alternative, the criteria value of the alternatives are calculated by the equation (1).

$$\tilde{x}_{ij} = \frac{1}{K} \left[\tilde{x}_{ij}^1 (+) \tilde{x}_{ij}^2 (+) \dots (+) \tilde{x}_{ij}^K \right] \quad (1)$$

Step 2: In a group composed of K decision makers where \tilde{w}_j^K demonstrates the importance weight of j . decision criteria, the importance weights of decision criteria are calculated using the equation (2).

$$\tilde{w}_j = \frac{1}{K} \left[\tilde{w}_j^1 (+) \tilde{w}_j^2 (+) \dots (+) \tilde{w}_j^K \right] \quad (2)$$

As stated above, matrix format of a multi-criteria decision making problem can be expressed as follows:

$$\tilde{D} = \begin{matrix} & C_1 & C_2 & \dots & C_n \\ \begin{matrix} A_1 \\ A_2 \\ \vdots \\ A_m \end{matrix} & \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \dots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \dots & \tilde{x}_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \dots & \tilde{x}_{mn} \end{bmatrix} \end{matrix}, \quad \tilde{W} = [\tilde{w}_1 \quad \tilde{w}_2 \quad \dots \quad \tilde{w}_n] \quad (3)$$

where $A_1; A_2; A_m$ are possible alternatives among which decision makers have to choose, C_1, C_2, \dots, C_n are decision criteria with which alternative performance are measured, x_{ij} is the rating of alternative A_i with respect to criterion C_j ; w_j is the weight of criterion C_j .

These linguistic variables are expressed with triangular fuzzy numbers as $\tilde{x}_{ij} = (a_{ij}, b_{ij}, c_{ij})$, and $\tilde{w}_j = (w_{j1}, w_{j2}, w_{j3})$. The matrix \tilde{D} is called fuzzy decision matrix and \tilde{W} matrix is called as fuzzy weight matrix.

Step 3: The normalized fuzzy decision matrix obtained from fuzzy decision matrix is denoted by

$$\tilde{R} = [\tilde{r}_{ij}]_{m \times n} \quad (4)$$

In this equation, \tilde{r}_{ij} is calculated by the following equations

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*} \right), \quad j \in B, \quad c_j^* = \max_i c_{ij}, \quad (5)$$

or

$$\tilde{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}} \right), \quad j \in C, \quad a_j^- = \min_i a_{ij}, \quad (6)$$

where B and C are the set of benefit criteria and cost criteria respectively.

The normalization method mentioned above is to preserve the property that the ranges of normalized triangular fuzzy numbers belong to [0, 1].

Step 4: Considering the different importance of each decision criterion, the weighted normalized fuzzy decision matrix can be constructed as

$$\tilde{V} = [\tilde{v}_{ij}]_{m \times n}, \quad i=1,2,\dots,m; j=1,2,\dots,n \quad (7)$$

where

$$\tilde{v}_{ij} = \tilde{r}_{ij}(\cdot) \tilde{w}_j \quad (8)$$

The weighted normalized fuzzy decision matrix is calculated by multiplying normalized fuzzy decision matrix and fuzzy weighted matrix. According to the weighted normalized fuzzy decision matrix for $\forall_{i,j}$ the elements of \tilde{v}_{ij} are normalized triangular fuzzy numbers belonging to [0, 1].

Step 5: Fuzzy positive-ideal solution (FPIS) can be defined as,

$$A^* = (\tilde{v}_1^*, \tilde{v}_2^*, \dots, \tilde{v}_n^*), \quad (9)$$

and fuzzy negative-ideal solution (FNIS) can be defined as

$$A^- = (\tilde{v}_1^-, \tilde{v}_2^-, \dots, \tilde{v}_n^-), \quad (10)$$

where $\tilde{v}_j^* = (1, 1, 1)$, $\tilde{v}_j^- = (0, 0, 0)$, and $j = 1, 2, 3, \dots, n$. The number of the FPIS and FNIS is equal to the number of the decision criteria.

The distance of the each alternative from positive-ideal solution and negative-ideal solution can respectively be calculated by the following equations

$$d_i^* = \sum_{j=1}^n d(\tilde{v}_{ij}, \tilde{v}_j^*) \quad , i=1, 2, \dots, m \quad (11)$$

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

where $d(.,.)$ indicates the distance between two fuzzy numbers and is calculated by Vertex Method.

Assume that $\tilde{a} = (a_1, a_2, a_3)$, and $\tilde{b} = (b_1, b_2, b_3)$ are two triangular fuzzy numbers then the calculation of the distance measurement between these by Vertex Method (proposed by Chen) is as in the Equation (13)

$$d(\tilde{a}, \tilde{b}) = \sqrt{\frac{1}{3} [(a_1 - b_1)^2 + (a_2 - b_2)^2 + (a_3 - b_3)^2]} \quad (13)$$

Step 6: The closeness coefficient is calculated using the following equation.

$$CC_i = \frac{d_i^-}{d_i^* + d_i^-} \quad , i=1, 2, \dots, m \quad (14)$$

Closeness coefficient values are between 0 and 1 and alternatives are ranked by these values. The alternative with the greatest closeness coefficient is chosen because it means the alternative is the closest to the positive-ideal solution and farthest from the negative-ideal solution.

4. AN EMPIRICAL APPLICATION

The firm included in the study has been operating in construction sector since 1970. It is one of the biggest firms of Turkey and in this context it is in the list of “First 500 Big Industrial Organizations of Turkey” being published every year. The first conversations were made with the human resource manager of the firm. The cooperation was for machine maintenance manager position. After the preliminary screening of the human resource department six candidates were found to be appropriate for the interview step of the selection process. The candidates were evaluated in the interview by the committee composed of three decision makers (D_1 , D_2 , and D_3). The titles of these are general manager, regional director, and human resource manager.

Twelve benefit criteria (C_1 : self-reliance, C_2 : expression of himself, C_3 : speaking fluently, honestly with a wide range of vocabulary, C_4 : usage of body language, C_5 : capacity to understand and judge, C_6 : time management, C_7 : communication, C_8 : capacity of listening, C_9 : business knowledge, C_{10} : experience, C_{11} : comment of the reference, C_{12} : evaluation of the curriculum vitae) and importance weight of each of them were predetermined by the human resource management team. Linguistic variables and their triangular fuzzy number equivalents for the importance weight of each criterion used in this paper are shown in Table 2.

Table 2. Linguistic Variables for Importance Weight of Each Criterion

Very Low (VL)	(0, 0, 0.2)
Low (L)	(0, 0.2, 0.4)
Medium (M)	(0.3, 0.5, 0.7)
High (H)	(0.6, 0.8, 1)
Very High (VH)	(0.8, 1, 1)

The linguistic evaluation of the human resource management team (shown in Table 3) for the importance weights of each criterion were transformed into triangular fuzzy numbers by using Table 2. The obtained fuzzy weight matrix is shown in Table 4.

Table 3. Linguistic Evaluation for the Importance Weight of Each Criterion

Criteria (C)	Linguistic Evaluation for the Importance Weight of Each Criterion
C ₁	H
C ₂	H
C ₃	H
C ₄	H
C ₅	VH
C ₆	VH
C ₇	VH
C ₈	H
C ₉	VH
C ₁₀	VH
C ₁₁	H
C ₁₂	VH

Table 4. Fuzzy Weight Matrix

Criteria (C)	
C ₁	(0.600, 0.800, 1.000)
C ₂	(0.600, 0.800, 1.000)
C ₃	(0.600, 0.800, 1.000)
C ₄	(0.600, 0.800, 1.000)
C ₅	(0.800, 1.000, 1.000)
C ₆	(0.800, 1.000, 1.000)
C ₇	(0.800, 1.000, 1.000)
C ₈	(0.600, 0.800, 1.000)
C ₉	(0.800, 1.000, 1.000)
C ₁₀	(0.800, 1.000, 1.000)
C ₁₁	(0.600, 0.800, 1.000)
C ₁₂	(0.800, 1.000, 1.000)

Table 5. Linguistic Variables Used for the Evaluation of the Candidates

Very Poor (VP)	(0, 0, 2)
Poor (P)	(0, 2, 4)
Fair (F)	(3, 5, 7)
Good (G)	(6, 8, 10)
Very Good (VG)	(8, 10, 10)

Then three decision makers evaluated the candidates with respect to the predetermined criteria for the machine maintenance manager position one by one by using the linguistic variables shown in Table 5. The results of the interview performance evaluations are shown in Table 6.

Table 6. Evaluation of the Candidates by Three Decision Makers

Alternatives (A)	Criteria (C) 1. Decision Maker											
	C ₁	C ₂	C ₃	C ₄	C ₅	C ₆	C ₇	C ₈	C ₉	C ₁₀	C ₁₁	C ₁₂
A ₁	G	G	G	G	VG	G	VG	VG	VG	VG	VG	VG
A ₂	VG	VG	G	F	G	G	G	VG	VG	G	G	VG
A ₃	G	G	F	F	G	F	F	F	G	G	G	G
A ₄	VG	VG	VG	VG	VG	G	VG	VG	VG	G	VG	VG
A ₅	F	F	P	F	G	F	G	G	G	F	G	G
A ₆	F	P	F	F	P	G	F	G	G	G	G	G
Alternatives (A)	Criteria (C) 2. Decision Maker											
	C ₁	C ₂	C ₃	C ₄	C ₅	C ₆	C ₇	C ₈	C ₉	C ₁₀	C ₁₁	C ₁₂
A ₁	VG	VG	VG	G	G	G	G	VG	VG	VG	VG	VG
A ₂	G	G	G	F	VG	G	VG	VG	G	G	G	VG
A ₃	F	F	F	F	G	F	F	F	G	G	F	G
A ₄	VG	G	VG	VG	G	F	G	VG	G	VG	VG	VG
A ₅	P	F	F	G	G	F	G	F	F	F	F	G
A ₆	G	F	F	F	F	G	F	F	G	F	G	G
Alternatives (A)	Criteria (C) 3. Decision Maker											
	C ₁	C ₂	C ₃	C ₄	C ₅	C ₆	C ₇	C ₈	C ₉	C ₁₀	C ₁₁	C ₁₂
A ₁	G	VG	VG	G	VG	G	G	G	F	VG	VG	VG
A ₂	VG	VG	F	G	G	F	G	G	VG	VG	G	VG
A ₃	G	F	G	G	G	F	G	G	F	G	G	G
A ₄	G	G	VG	G	VG	F	VG	G	VG	G	G	VG
A ₅	P	P	F	F	F	F	F	P	F	F	F	G
A ₆	F	P	F	F	P	F	F	G	G	G	G	G

For the next step of the algorithm, fuzzy decision matrix was formed by using Table 5, Table 6 and Equation (1). Fuzzy decision matrix is shown in Table 7.

Table 7. Fuzzy Decision Matrix

Alternatives (A)	Criteria (C)			
	C ₁	C ₂	C ₃	C ₄
A ₁	(6.667, 8.667, 10.000)	(7.333, 9.333, 10.000)	(7.333, 9.333, 10.000)	(6.000, 8.000, 10.000)
A ₂	(7.333, 9.333, 10.000)	(7.333, 9.333, 10.000)	(5.000, 7.000, 9.000)	(4.000, 6.000, 8.000)
A ₃	(5.000, 7.000, 9.000)	(4.000, 6.000, 8.000)	(4.000, 6.000, 8.000)	(4.000, 6.000, 8.000)
A ₄	(7.333, 9.333, 10.000)	(6.667, 8.667, 10.000)	(8.000, 10.000, 10.000)	(7.333, 9.333, 10.000)
A ₅	(1.000, 3.000, 5.000)	(2.000, 4.000, 6.000)	(2.000, 4.000, 6.000)	(4.000, 6.000, 8.000)
A ₆	(4.000, 6.000, 8.000)	(1.000, 3.000, 5.000)	(3.000, 5.000, 7.000)	(3.000, 5.000, 7.000)
Alternatives (A)	Criteria (C)			
	C ₅	C ₆	C ₇	C ₈
A ₁	(7.333, 9.333, 10.000)	(6.000, 8.000, 10.000)	(6.667, 8.667, 10.000)	(7.333, 9.333, 10.000)
A ₂	(6.667, 8.667, 10.000)	(5.000, 7.000, 9.000)	(6.667, 8.667, 10.000)	(7.333, 9.333, 10.000)
A ₃	(6.000, 8.000, 10.000)	(3.000, 5.000, 7.000)	(4.000, 6.000, 8.000)	(4.000, 6.000, 8.000)
A ₄	(7.333, 9.333, 10.000)	(4.000, 6.000, 8.000)	(7.333, 9.333, 10.000)	(7.333, 9.333, 10.000)
A ₅	(5.000, 7.000, 9.000)	(3.000, 5.000, 7.000)	(5.000, 7.000, 9.000)	(3.000, 5.000, 7.000)
A ₆	(1.000, 3.000, 5.000)	(5.000, 7.000, 9.000)	(3.000, 5.000, 7.000)	(5.000, 7.000, 9.000)
Alternatives (A)	Criteria (C)			
	C ₉	C ₁₀	C ₁₁	C ₁₂
A ₁	(6.333, 8.333, 9.000)	(8.000, 10.000, 10.000)	(8.000, 10.000, 10.000)	(8.000, 10.000, 10.000)
A ₂	(7.333, 9.333, 10.000)	(6.667, 8.667, 10.000)	(6.000, 8.000, 10.000)	(8.000, 10.000, 10.000)
A ₃	(5.000, 7.000, 9.000)	(6.000, 8.000, 10.000)	(5.000, 7.000, 9.000)	(6.000, 8.000, 10.000)
A ₄	(7.333, 9.333, 10.000)	(6.667, 8.667, 10.000)	(7.333, 9.333, 10.000)	(8.000, 10.000, 10.000)
A ₅	(4.000, 6.000, 8.000)	(3.000, 5.000, 7.000)	(4.000, 6.000, 8.000)	(6.000, 8.000, 10.000)
A ₆	(6.000, 8.000, 10.000)	(5.000, 7.000, 9.000)	(6.000, 8.000, 10.000)	(6.000, 8.000, 10.000)

The normalized fuzzy decision matrix and weighted normalized fuzzy decision matrix were formed as in Table 8 and Table 9 respectively.

Table 8. Normalized Fuzzy Decision Matrix

Alternatives (A)	Criteria (C)			
	C ₁	C ₂	C ₃	C ₄
A ₁	(0.667, 0.867, 1.000)	(0.733, 0.933, 1.000)	(0.733, 0.933, 1.000)	(0.600, 0.800, 1.000)
A ₂	(0.733, 0.933, 1.000)	(0.733, 0.933, 1.000)	(0.500, 0.700, 0.900)	(0.400, 0.600, 0.800)
A ₃	(0.500, 0.700, 0.900)	(0.400, 0.600, 0.800)	(0.400, 0.600, 0.800)	(0.400, 0.600, 0.800)
A ₄	(0.733, 0.933, 1.000)	(0.667, 0.867, 1.000)	(0.800, 1.000, 1.000)	(0.733, 0.933, 1.000)
A ₅	(0.100, 0.300, 0.500)	(0.200, 0.400, 0.600)	(0.200, 0.400, 0.600)	(0.400, 0.600, 0.800)
A ₆	(0.400, 0.600, 0.800)	(0.100, 0.300, 0.500)	(0.300, 0.500, 0.700)	(0.300, 0.500, 0.700)
Alternatives (A)	Criteria (C)			
	C ₅	C ₆	C ₇	C ₈
A ₁	(0.733, 0.933, 1.000)	(0.600, 0.800, 1.000)	(0.667, 0.867, 1.000)	(0.733, 0.933, 1.000)
A ₂	(0.667, 0.867, 1.000)	(0.500, 0.700, 0.900)	(0.667, 0.867, 1.000)	(0.733, 0.933, 1.000)
A ₃	(0.600, 0.800, 1.000)	(0.300, 0.500, 0.700)	(0.400, 0.600, 0.800)	(0.400, 0.600, 0.800)
A ₄	(0.733, 0.933, 1.000)	(0.400, 0.600, 0.800)	(0.733, 0.933, 1.000)	(0.733, 0.933, 1.000)
A ₅	(0.500, 0.700, 0.900)	(0.300, 0.500, 0.700)	(0.500, 0.700, 0.900)	(0.300, 0.500, 0.700)
A ₆	(0.100, 0.300, 0.500)	(0.500, 0.700, 0.900)	(0.300, 0.500, 0.700)	(0.500, 0.700, 0.900)
Alternatives (A)	Criteria (C)			
	C ₉	C ₁₀	C ₁₁	C ₁₂
A ₁	(0.633, 0.833, 0.900)	(0.800, 1.000, 1.000)	(0.800, 1.000, 1.000)	(0.800, 1.000, 1.000)
A ₂	(0.733, 0.933, 1.000)	(0.667, 0.867, 1.000)	(0.600, 0.800, 1.000)	(0.800, 1.000, 1.000)
A ₃	(0.500, 0.700, 0.900)	(0.600, 0.800, 1.000)	(0.500, 0.700, 0.900)	(0.600, 0.800, 1.000)
A ₄	(0.733, 0.933, 1.000)	(0.667, 0.867, 1.000)	(0.733, 0.933, 1.000)	(0.800, 1.000, 1.000)
A ₅	(0.400, 0.600, 0.800)	(0.300, 0.500, 0.700)	(0.400, 0.600, 0.800)	(0.600, 0.800, 1.000)
A ₆	(0.600, 0.800, 1.000)	(0.500, 0.700, 0.900)	(0.600, 0.800, 1.000)	(0.600, 0.800, 1.000)

Table 9. Weighted Normalized Fuzzy Decision Matrix

Alternatives (A)	Criteria (C)			
	C ₁	C ₂	C ₃	C ₄
A ₁	(0.400, 0.694, 1.000)	(0.440, 0.746, 1.000)	(0.440, 0.746, 1.000)	(0.360, 0.640, 1.000)
A ₂	(0.440, 0.746, 1.000)	(0.440, 0.746, 1.000)	(0.300, 0.560, 0.900)	(0.240, 0.480, 0.800)
A ₃	(0.300, 0.560, 0.900)	(0.240, 0.480, 0.800)	(0.240, 0.480, 0.800)	(0.240, 0.480, 0.800)
A ₄	(0.440, 0.746, 1.000)	(0.400, 0.694, 1.000)	(0.480, 0.800, 1.000)	(0.440, 0.746, 1.000)
A ₅	(0.060, 0.240, 0.500)	(0.120, 0.320, 0.600)	(0.120, 0.320, 0.600)	(0.240, 0.480, 0.800)
A ₆	(0.240, 0.480, 0.800)	(0.060, 0.240, 0.500)	(0.180, 0.400, 0.700)	(0.180, 0.400, 0.700)
Alternatives (A)	Criteria (C)			
	C ₅	C ₆	C ₇	C ₈
A ₁	(0.586, 0.933, 1.000)	(0.480, 0.800, 1.000)	(0.534, 0.867, 1.000)	(0.440, 0.746, 1.000)
A ₂	(0.534, 0.867, 1.000)	(0.400, 0.700, 0.900)	(0.534, 0.867, 1.000)	(0.440, 0.746, 1.000)
A ₃	(0.480, 0.800, 1.000)	(0.240, 0.500, 0.700)	(0.320, 0.600, 0.800)	(0.240, 0.480, 0.800)
A ₄	(0.586, 0.933, 1.000)	(0.320, 0.600, 0.800)	(0.586, 0.933, 1.000)	(0.440, 0.746, 1.000)
A ₅	(0.400, 0.700, 0.900)	(0.240, 0.500, 0.700)	(0.400, 0.700, 0.900)	(0.180, 0.400, 0.700)
A ₆	(0.080, 0.300, 0.500)	(0.400, 0.700, 0.900)	(0.240, 0.500, 0.700)	(0.300, 0.560, 0.900)
Alternatives (A)	Criteria (C)			
	C ₉	C ₁₀	C ₁₁	C ₁₂
A ₁	(0.506, 0.833, 0.900)	(0.640, 1.000, 1.000)	(0.480, 0.800, 1.000)	(0.640, 1.000, 1.000)
A ₂	(0.586, 0.933, 1.000)	(0.534, 0.867, 1.000)	(0.360, 0.640, 1.000)	(0.640, 1.000, 1.000)
A ₃	(0.400, 0.700, 0.900)	(0.480, 0.800, 1.000)	(0.300, 0.560, 0.900)	(0.480, 0.800, 1.000)
A ₄	(0.586, 0.933, 1.000)	(0.534, 0.867, 1.000)	(0.440, 0.746, 1.000)	(0.640, 1.000, 1.000)
A ₅	(0.320, 0.600, 0.800)	(0.240, 0.500, 0.700)	(0.240, 0.480, 0.800)	(0.480, 0.800, 1.000)
A ₆	(0.480, 0.800, 1.000)	(0.400, 0.700, 0.900)	(0.360, 0.640, 1.000)	(0.480, 0.800, 1.000)

After the formation of weighted normalized fuzzy decision matrix (it is accepted that $\tilde{v}_j^+ = (1,1,1)$ and $\tilde{v}_j^- = (0,0,0)$ in the study) the distance of the candidates from the fuzzy positive ideal solutions and negative ideal solutions were calculated (shown in Table 10).

Table 10. The Distances of the Candidates from the FPIS and FNIS

Alternatives (A)	d^*	d^-
A ₁	3.765	9.567
A ₂	4.193	9.125
A ₃	5.515	7.683
A ₄	3.816	9.488
A ₅	6.500	6.531
A ₆	6.132	7.011

Finally, closeness coefficients of the candidates were calculated and ranks of the candidates were determined as A₁, A₄, A₂, A₃, A₆, A₅. It can be seen from Table 11.

Table 11. Closeness Coefficients and Candidate Ranks

Alternatives (A)	Closeness Coefficients	Ranks
A ₁	0.718	1
A ₂	0.685	3
A ₃	0.582	4
A ₄	0.713	2
A ₅	0.501	6
A ₆	0.533	5

5. CONCLUSION

Directing all the other inputs by his knowledge, the priority of “human”, the most important resource of business organizations, has become even more highlighted in conjunction with the Information Age. Today, to have qualified human resources reflecting his full capacity to his work in cooperation and human resource applications that makes it possible are important for a business organization for gaining sustainable competitive advantage and standing in the first ranks of its sector. In this context, human resource selection problem is a strategic issue. Therefore, an effective decision making approach is essential to eliminate both uncertainty of this process being derived from verbal data and

subjectivity arising from the process's being based on decision maker's intuition. For this reason, in this paper, fuzzy TOPSIS method as a fuzzy multi-criteria decision making approach is used for human resource selection process in which there is an evaluation with respect to various criteria and finally group decision is made. The study presents an application of a business organization's interview process conducted for machine maintenance manager position. In fuzzy TOPSIS decision makers used the linguistic variables to assess the importance of the criteria and to evaluate the each candidate for the machine maintenance position with respect to each criterion. These linguistic variables were transformed into triangular fuzzy numbers and fuzzy decision matrix was formed. Then normalized fuzzy decision matrix and weighted normalized fuzzy decision matrix were formed. After FPIS and FNIS were defined, distance of each candidate to FPIS and FNIS were calculated. And then the closeness coefficient of each candidate was calculated separately. According to the closeness coefficient of three candidates, the ranking order of six candidates has been determined as $A_1 > A_4 > A_2 > A_3 > A_6 > A_5$.

The important contribution of this study to the literature has been considered as that our application is based on a business organization in the list of "First 500 Big Industrial Organizations of Turkey". So, it can be said that this study shows a personnel recruitment system of an institutional structure. It is possible to increase the number of empirical applications for the other positions to introduce the fuzzy multi-criteria decision making methods and generalize the usage of them. Expert systems such as fuzzy logic can bring a new insight to human resource selection process which has great importance for the organizations and also affects the future performance of them. More effective decisions can be available with such fuzzy modeling techniques. And also it is possible to eliminate the subjectivity of the process.

In future studies, other multi-criteria methods like fuzzy PROMETHEE, ELECTRE and other fuzzy modeling techniques such as adaptive network based fuzzy logic can be used to handle human resource selection problems. And also the proposed methods can be applied to other multi-criteria decision problems in the field of human resource management like job evaluation and performance evaluation.

6. REFERENCES

AYUB, M., Kabir, Md. J. & Alam, Md. G. R. (2009). "Personnel Selection Method Using Analytic Network Process (ANP) and Fuzzy Concept", **Proceedings of 12th International Conference on Computer and Information Technology**, December 21-23, Dhaka, pp. 373-378.

CHANG, J. R., Ho, T. H., Cheng, C. H. & Chen, A. P. (2006). "Dynamic Fuzzy OWA Model for Group Multiple Criteria Decision Making", **Soft Computing**, 10, pp. 543-554.

CHEN, P. C. (2009). "A Fuzzy Multiple Criteria Decision Making Model in Employee Recruitment", **International Journal Of Computer Science and Network Society**, 9 (7), pp. 113-117.

DURSUN, M. & Karsak, E. E. (2010). "A Fuzzy MCDM Approach for Personnel Selection", **Expert Systems with Applications**, 37, pp. 4324-4330.

ERGİNEL, N., Çakmak, T. & Şentürk, S. (2010). "After Number Portability Application Determination of GSM Operator Preferences in Turkey with Fuzzy TOPSIS Approach", **Anadolu University Science and Technology Journal**, 11 (2), pp. 81-93.

GOLEC, A. & Kahya, E. (2007). "A Fuzzy Model for Competency-Based Employee Evaluation and Selection", **Computers & Industrial Engineering**, 52, pp. 143-161.

KARSAK, E. E. (2001). "Personnel Selection Using a Fuzzy MCDM Approach Based on Ideal and Anti-Ideal Solutions, (Edited by: Murat Köksalan and Stanley Zionts), **Multi Criteria Decision Making in the New Millennium**, Springer-Verlag London Limited, London, pp. 393-402.

KELEMENIS, A., Ergazakis, K. & Askounis, D. (2011). "Support Managers' Selection Using an Extension of Fuzzy Topsis", **Expert Systems with Applications**, 38, pp. 2774-2782.

KWAK, W., Shi, Y. & Jung, K. (2003). "Human Resource Allocation in a CPA Firm: A Fuzzy Set Approach", **Review of Quantitative Finance and Accounting**, 20, pp. 277-290.

KWAK, W. (2010). "A Fuzzy Set Approach in Audit Staff Planning Problems", <http://www.wseas.us/e-library/conferences/jamaica2000/papers/157.pdf>, (21.12.2010).

LIN, H. (2010). "Personnel Selection Using Analytic Network Process and Fuzzy Data Envelopment Analysis Approaches", **Computers & Industrial Engineering**, 59, pp. 937-944.

PETROVIC-LAZAREVIC, S. (2001). "Personnel Selection Fuzzy Model", **International Transactions in Operational Research**, 8, pp. 89-105.

RAMADAN, M. Z.(2009). "Effective Staff Selection Tool: Fuzzy Numbers and Memetic Algorithm Based Approach", **International Journal of Engineering & Technology**, 9 (10), pp. 54-65.

SAATY, T. L. & Vargas, L. G. (2006). **Decision Making with the Analytic Network Process: Economic, Political, Social, and Technological Applications with Benefits, Opportunities, Cost, and Risks**, Springer Science+Business Media, New York.

ZADEH, A. L. (1975). "The Concept of Linguistic Variable and Its Application to Approximate Reasoning –I", **Information Sciences**, 8, pp. 199-249.

CHEN, C. (2000). "Extensions of the TOPSIS for Group Decision Making Under Fuzzy Environment", **Fuzzy Sets and Systems**, 114, pp. 1-9.

WANG, Y. M. & Elhag, T. M. S. (2006). "Fuzzy TOPSIS Method Based on Alpha Level Sets with an Application to Bridge Risk Assessment", **Expert Systems with Applications**, 31, pp. 309-319.