Journal homepage: www.jmisci.com
Contact: editor@jmisci.com

Journal of Military and Information Science
Institute of Science

JMIS

A Group MADM Method for Personnel Selection Problem Using Delphi Technique Based on Intuitionistic Fuzzy Sets

Özkan Bali*, Serkan Gümüş**, Metin Dağdeviren***

* Defense Sciences Institute, Turkish Military Academy, 06654, Ankara, Turkey, E-mail: obali@kho.edu.tr
** Department of Basic Sciences, Turkish Military Academy, 06654, Ankara, Turkey, E-mail: sgumus@kho.edu.tr
*** Department of Industrial Engineering, Gazi University, Maltepe, 06570, Ankara, Turkey, E-mail: metindag@gazi.edu.tr

‡ Corresponding Author: Özkan Bali; Address: Kara Harp Okulu, Savunma Bilimleri Enstitüsü Bakanlıklar Ankara Turkey, Tel: +90 312 417 5190, Fax: +90 312 419 0265, e-mail: obali@kho.edu.tr

Abstract. Personnel selection (PS) is an important problem for an organization while the competition in global markets increases. PS, is a decision making process consisting of vagueness and imprecision. In real world, decision makers' experience, position through the organization, effectiveness in the group and field of expertise for each attribute in the group influence decision making process for PS. In this study, a group multi attribute decision making method has been developed using Delphi Technique based on intuitionistic fuzzy sets in sensitivity of experts to exploit the uncertainty and to take account of decision makers' importance for each attribute in the PS problem. The proposed method was applied in a case study. Case study showed that taking into account weights of decision makers for each attribute affect the result of the process of personnel selection.

Keywords: Delphi technique, group decision making, intuitionistic fuzzy sets, multi attribute decision making, personnel selection problem.

1. Introduction

Personnel selection (PS) is the period of selecting individuals who match the qualifications required to perform a job or to suit to a position. PS determines the input quality of personnel and plays a significant role in human resource management. It is a very important decision making process for an organization's success while the competition in global markets increases. To obtain and maintain competitive advantages for an organization depends on selecting right people in the right position at the right time.

Generally, a group of decision makers in PS process evaluate candidates with respect to determined attributes. Many individual attributes such as leadership, motivation, proficiency and appearance reveal vagueness and imprecision. PS depends on the organization's aims, features of job or position, attributes of selection and preferences of the decision makers. Owing to multi attributes, candidates and decision makers, PS is considered as a multi attribute decision making (MADM) problem. There are many studies which define PS as a MADM problem in the literature. Liang and Wang (1994) developed a fuzzy MCDM algorithm for PS that aggregates decision makers' linguistic assessments about subjective and objective criteria weights and ratings. Karsak (2001) presented a fuzzy MCDM framework based on the concepts of ideal and anti-ideal solutions for the selection of the most appropriate candidate. Li (2007) developed a new fuzzy proximity methodology for multi-attribute decision making and used this method in a real example of a PS problem. Güngör et al. (2009) recommended fuzzy Analytic Hierarchy Process (AHP) method for PS problem and they compared their model, with Yager's ordered weighted averaging aggregation operators. Dursun and Karsak (2010) proposed a fuzzy MCDM 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). Kelemenis and Askounis (2010) considered TOPSIS, incorporating a new concept for the ranking of the alternatives. This is based on the veto threshold, a critical characteristic of the main outranking methods. Dağdeviren (2010) proposed a hybrid model which operates Analytic Network Process (ANP) and modified TOPSIS for the PS problem.

Some researches present fuzzy model for PS. Lazarevic (2001) presented a two-level employee selection fuzzy model to minimize subjective judgment in the process of distinguishing between an appropriate and inappropriate employee for a job position. A weight method which includes minimal error was developed by Jessop (2004) in PS. Göleç and Kahya (2007) presented a fuzzy model by the help of linguistic variables in order to select and evaluate a right employee. And some studies have presented decision support system for PS. Chen and Cheng (2005) suggested a fuzzy group decision support system based on metric distance method to solve information system in PS problem. Malinowski et al. (2008) presented a decision support system based on a relational recommendation approach for providing an automated pre-selection of candidates that fit best with future team members. Chien and Chen (2008) aimed to fill the gap by developing a data mining framework based on decision tree and association rules to generate useful rules for PS. The results can provide decision rules relating personnel information with work performance and retention. Huang et al. (2009) presented an integrated method for solving the personnel assignment problem. The interdependences among positions are involved, and the differences among employees are taken into consideration. Lin (2010) developed a decision support tool using ANP and fuzzy data envelopment analysis (DEA) approach to effectively deal with the PS problem. Zhang and Liu (2011) proposed an intuitionistic fuzzy multi-criteria group decision making method with grey relational analysis (GRA) to choose the best candidate in PS problem.

To the our best knowledge, decision makers' experience, position through the organization, effectiveness in the group and profession for each attribute have not been considered in the studies done on PS up to now. However, in real world such specialties of decision makers should be important in decision making process and affect the choosing of best candidate. Generally, the others are influenced from the decision maker who has the higher importance for each attribute while they evaluate the candidates. Moreover, evaluation of a decision maker performed in accordance with the attribute in his field of expertise is more significant than the other decision makers. In other words, in the group decision making process decision makers are influenced by the other group members while evaluating the candidates. In this study, we assumed that the importance and weights of decision makers are different for each attribute in PS problem. In this point, we face determination of weights of decision makers for each attribute. Therefore, we utilize Delphi Technique. Moreover, we use this technique to determine decision makers and attributes, and to calculate weights of attributes. On the other hand, due to fact that PS process consists of uncertainty, we benefit from intuitionistic fuzzy sets (IFS). The IFS theory appears as an important tool to provide a decision problem that includes imprecise judgments inherent in the PS. To sum up, in this study, a group MADM method has been developed using Delphi Technique based on IFSs in sensitivity of experts to resolve the uncertainty and to take account of decision makers' importance for each attribute in the PS problem.

The rest of the paper is organized as follows: Section 2 gives knowledge of Delphi Technique. IFSs and its literature are presented in Section 3. Sections 4 outline the proposed group MADM method for PS problem. In Section 5, it can be seen the application of the proposed method on a case study. Finally, conclusion is given in Section 6.

2. Delphi Technique

The RAND Corporation developed the Delphi method to collect the most reliable data from a structured expert group about an issue (Dalkey and Halmer, 1963). Delphi method is an iterative and systematic process to obtain data related to the issue by using experts' judgments. Generally, there are two or three iterations in this method. After each iteration, experts are given statistical or summary feedback on previous iteration. Thus, they are provided with the opportunity to modify their judgments. It is expected that modified judgments of experts reflect agreement or disagreement about the issue. Therefore, the differences of the judgments diminish, and they converge towards an anonymous judgment during the process. It is believed that experts come to an agreement on the issue and they achieve consensus in the end of the process. Delphi method has been used for many MADM problems such as Handfield et al. (2002), Chang et al. (2007), Gerdsri and Kocaoglu (2007), Shen et al. (2010), Tavana et al. (2012).

3. Intuitionistic Fuzzy Sets

IFSs were introduced by Atanassov (1986, 1999), which is an extension of the classical Fuzzy Set Theory, is a suitable way to deal with vagueness. IFSs have been applied to many decision making problems in the literature. Chen and Tan (1994) handled multi-criteria fuzzy decision-making problems by using vague set theory. Triantaphyllou and Lin (1996) developed fuzzy multi attribute decision making methods. Hong and Choi (2000) introduced new methods for multi-criteria fuzzy decision making problems by using vague set theory. They provided new functions to measure the degree of accuracy in the grades of membership of each alternative with respect to a set of criteria. However, they assumed that the degree of importance to each attribute is constant; Chen (2000) presented extension methods in the TOPSIS for group decision making with using fuzzy theory. Szmidt and Kacprzyk (2002, 2003) worked on group decision making problem with IFS theory. Atanassov, Pasi and Yager (2005) developed intuitionistic fuzzy interpretations of multi-criteria, multi-person and multi-measurement tool decision making. Jahanshahlo, Hosseinzade and Izadikhah (2006a, 2006b) extended an algorithmic method in the TOPSIS for decision making problems with interval data. Liu and Wang (2007) mainly focused on the Chen and Tan's problem to illustrate the application of IFSs to multicriteria decision-making. Liu, Huan and Xia (2007) presented a new method for handling multicriteria fuzzy decision-making problems based on IFSs. The proposed method used the truth-membership function and non-truth-membership function to indicate the degrees of satisfiability and non-satisfiability of each alternative with respect to a set of criteria, respectively. Xu (2007a, 2007b) established intuitionistic fuzzy aggregation operators and he gave some applications in decision making with IFS theory. The other studies, which have been applied to decision making problem with based on intuitionsitic fuzzy set theory, are Wang (2009) and Boran et. al. (2009). Xu and Cai (2010) surveyed the aggregation techniques of intuitionistic fuzzy information, and their applications in various fields, such as decision making, cluster analysis, medical diagnosis, forecasting, and manufacturing grid.

In the following, some definitions are presented on IFS.

Definition 1 : Let X be a nonempty fixed set and I the closed unit interval [0,1]. An IFS A is an object having the form

$$A = \{(x, \mu_A(x), \nu_A(x)) \mid x \in X\} \tag{1}$$

where the mappings $\mu_A : X \to I$ and $\nu_A : X \to I$ denote the degree of membership (namely, $\mu_A(x)$) and the degree of non-membership (namely, $\nu_A(x)$) of each element $x \in X$ to the set A, respectively, and

$0 \leq \mu_A(x) + \nu_A(x) \leq 1$ for each $x \in X$. Obviously, every fuzzy set *A* on a nonempty set *X* is an IFS having the form

$$A = \{(x, \mu_A(x), 1-\mu_A(x)) \mid x \in X\}.$$

For a given nonempty set *X*, denote the family of all IFSs in *X* by the symbol IFS(*X*).

Definition 2: Let *X* be a nonempty fixed set and $A \in$ IFS(*X*), intuitionistic fuzzy hesitation degree is defined as follows;

$$\pi_A(x) = 1 - \mu_A(x) - \nu_A(x) \qquad (2)$$

This degree is used for determining whether *x* belongs to *A* or not. Especially, if

$$\pi_A(x) = 1 - \mu_A(x) - \nu_A(x) = 0, \text{ for every } x \in X$$

then the IFS *A* reduced to a fuzzy set. In ddition, we can say $0 \leq \pi_A(x) \leq 1$.

Definition 3: We call $\alpha = (\mu_A(x), \nu_A(x), \pi_A(x))$ an intuitionistic fuzzy number (IFN), where $\mu_A(x) \in [0,1]$, $\nu_A(x) \in [0,1]$, $0 \leq \mu_A(x) + \nu_A(x) \leq 1$ and $\pi_A(x) = 1 - \mu_A(x) - \nu_A(x)$.

Definition 4: *A*, *B* is two IFSs in *X*. Some relations between IFSs are defined as follows:

(i) $A \subset B$ iff $\mu_A(x) \leq \mu_B(x)$ *and* $\nu_A(x) \geq \nu_B(x)$, for all $x \in X$

(ii) *A*=*B* iff $\mu_A(x) = \mu_B(x)$ *and* $\nu_A(x) = \nu_B(x)$, for all $x \in X$

(iii) $A \cap B$ $=\{\langle x, \min(\mu_A(x), \mu_B(x)), \max(\nu_A(x), \nu_B(x))\rangle \mid x \in X\}$

(iv) $A \cup B$ $=\{\langle x, \max(\mu_A(x), \mu_B(x)), \min(\nu_A(x), \nu_B(x))\rangle \mid x \in X\}$

(v) $A \otimes B =$ $\{\langle x, \mu_A(x).\mu_B(x), \nu_A(x) + \nu_B(x) - \nu_A(x).\nu_B(x)\rangle \mid x \in X\}$

Definition 5: Let $\alpha_1 = (\mu_{\alpha_1}, \nu_{\alpha_1}, \pi_{\alpha_1})$ and $\alpha_2 = (\mu_{\alpha_2}, \nu_{\alpha_2}, \pi_{\alpha_2})$ be two IFNs. The distance between α_1 and α_2 by Eq. 3 (Szmidt and Kacprzyk, 2000):

$$d(\alpha_1, \alpha_2) = \left\{ \frac{1}{2n} \sum_{j=1}^{n} \left[\begin{array}{l} \left(\mu_{\alpha_1} - \mu_{\alpha_2}\right)^2 + \\ \left(\nu_{\alpha_1} - \nu_{\alpha_2}\right)^2 + \left(\pi_{\alpha_1} - \pi_{\alpha_2}\right)^2 \end{array} \right] \right\}^{1/2} \qquad (3)$$

4. The proposed method for personnel selection problem

In this section, we consider personnel selection as a group MADM problem under uncertainty. Therefore, we propose a group MADM method using Delphi Technique based on IFS that is represented by IFNs. Let x_i, $i = 1,2,...,m$ is a discrete set of *m* feasible candidates, a_j, $j = 1,2,...,n$ is a finite set of *n* attributes and δ_k, $k = 1,2,...,t$ is a set of *t* decision makers in any personnel selection problem. The proposed method is applied in the following steps. Figure 1 shows the steps of the proposed method for personnel selection problem.

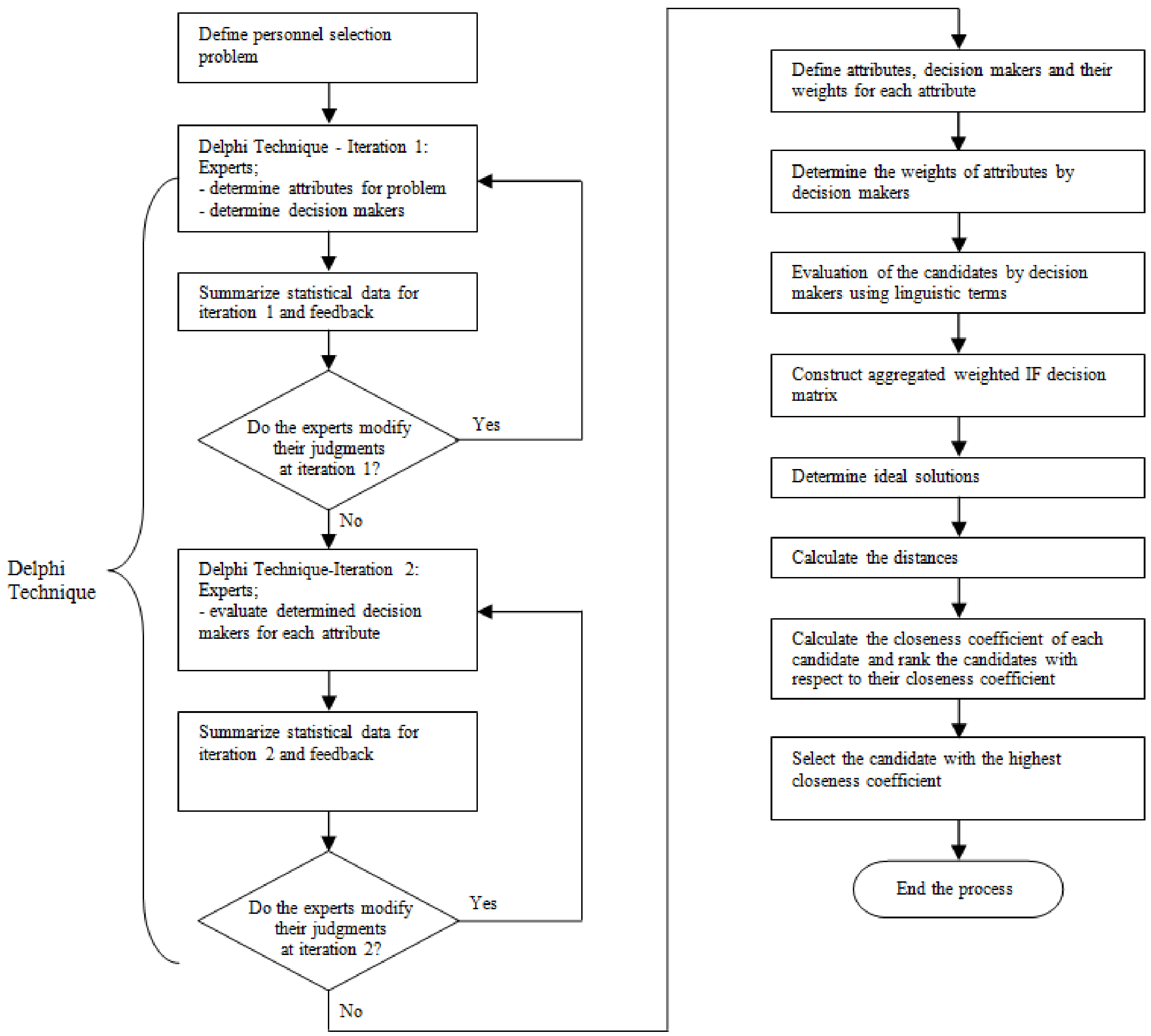

Fig. 1. Steps of the proposed method for personnel selection problem

Step 1: Define personnel selection problem.

Step 2: Apply Delphi Technique.

First of all, experts who will judge the problem are determined.

Step 2.1. Experts are asked open-ended questions to identify attributes and decision makers at iteration 1.

Step 2.1.1. Experts' judgments are summarized and they are given feedback.

Step 2.1.2. They are asked whether they will modify their judgments or not. It is expected that consensus is achieved among the experts about attributes and decision makers at the end of iteration 1.

Step 2.2. Experts are asked question to evaluate the determined decision makers using linguistic terms that are represented by IFNs at iteration 2.

Step 2.2.1. The evaluation received from experts is summarized and they are given feedback.

Step 2.2.2. They are asked whether they will modify their evaluation or not. It is expected that consensus is achieved among the experts about the evaluation of decision makers at the end of iteration 2.

Bali, Ö., Gümüş, S., Dağdeviren, M.(2013). A Group MADM Method for Personnel Selection Problem Using Delphi Technique Based on Intuitionistic Fuzzy Sets, Journal of Military and Information Science, 1(1), 1-13

Step 3: Define attributes, decision makers and calculate the weights of decision makers for each attribute.

As a result of implementation of the Delphi technique, *t* decision makers and *n* attributes to be used for the personnel selection are obtained. According to evaluations of decision makers, the weights of decision makers for each attribute ($\delta_j^{(k)}$) are calculated using Eq. 4. Let $\left(\mu_j^{(k)}, \nu_j^{(k)}, \pi_j^{(k)}\right)$ be an IFN for *j* th attribute of *k* th decision maker. Then the value $\delta_j^{(k)}$, which is weight of *j* th attribute of *k* th decision maker, can be obtained as;

$$\delta_j^{(k)} = \frac{\mu_j^{(k)} / (\mu_j^{(k)} + \nu_j^{(k)})}{\sum_{k=1}^{t} (\mu_j^{(k)} / (\mu_j^{(k)} + \nu_j^{(k)}))} \quad \text{and} \quad \sum_{k=1}^{t} \delta_j^{(k)} = 1,$$

$$\delta_j^{(k)} \in [0,1] \quad k = 1,2,\dots,t \tag{4}$$

Step 4: Determine the weights of attributes by decision makers.

Decision makers determine the importance of each attribute. *W* which is the matrix of weights of attributes, is calculated by taking the weights of decision makers into account. Let $w_j^{(k)} = \left(\mu_j^{(k)}, \nu_j^{(k)}, \pi_j^{(k)}\right)$ be an IFN for evaluation of k^{th} decision maker for j^{th} attribute. Then, the weight of the j^{th} attribute is calculated by taking the weight of each decision maker for j^{th} attribute by Eq. 5. For calculating of the weights of attributes is used the intuitionistic fuzzy weighted averaging (IFWA) operator proposed by Xu (2007c):

$$w_j = IFWA_{\delta_{jk}}(w_j^{(1)}, w_j^2, \dots, w_j^{(t)}) = \delta_j^{(1)} w_j^{(1)}$$
$$\oplus \delta_j^{(2)} w_j^{(2)} \oplus \cdots \oplus \delta_j^{(t)} w_j^{(t)}$$
$$= [1 - \prod_{k=1}^{t} (1 - \mu_j^{(k)})^{\delta_j^{(k)}}, \prod_{k=1}^{t} (\nu_j^{(k)})^{\delta_j^{(k)}},$$
$$\prod_{k=1}^{t} (1 - \mu_j^{(k)})^{\delta_j^{(k)}} - \prod_{k=1}^{t} (\nu_j^{(k)})^{\delta_j^{(k)}}] \tag{5}$$

$W = [w_1, w_2, \dots, w_j]$, where
$w_j = (\mu_j, \nu_j, \pi_j), (j = 1,2,\dots,n)$.

Step 5: Evaluate candidates by decision makers.

Decision makers evaluate candidates for each attribute using linguistic terms.

Step 6: Construct aggregated weighted intuitionistic fuzzy decision matrix.

Let $R = [r_{ij}]_{mxn}$ is an intuitionistic fuzzy decision matrix of each decision maker. An aggregated intuitionistic fuzzy decision matrix is formed with respect to decision makers' evaluation. If the following recently developed IFWA operator presented as Eq. 6 is used to form this matrix;

$$r_{ij} = IFWA_{\delta_j^{(k)}}(r_{ij}^{(1)}, r_{ij}^{(2)}, \dots, r_{ij}^{(t)})$$
$$= \delta_j^{(1)} r_{ij}^{(1)} \oplus \delta_j^{(2)} r_{ij}^{(2)} \oplus \dots \oplus \delta_j^{(t)} r_{ij}^{(t)}$$
$$= \begin{pmatrix} 1 - \prod_{k=1}^{t} (1 - \mu_{ij}^{(k)})^{\delta_j^{(k)}}, \prod_{k=1}^{t} (\nu_{ij}^{(k)})^{\delta_j^{(k)}}, \\ \prod_{k=1}^{t} (1 - \mu_{ij}^{(k)})^{\delta_j^{(k)}} - \prod_{k=1}^{t} (\nu_{ij}^{(k)})^{\delta_j^{(k)}} \end{pmatrix} \tag{6}$$

Here $r_{ij} = \left(\mu_{A_{ij}}, \nu_{A_{ij}}, \pi_{A_{ij}}\right)$; ($i$=1,2,…,$m$) and ($j$=1,2,…,n). The aggregated intuitionistic fuzzy decision matrix can be defined as follows:

$$R = \left[r_{ij}\right]_{mxn} = \begin{bmatrix} r_{11} & r_{12} & r_{13} & \cdots & r_{1n} \\ r_{21} & r_{22} & r_{23} & \cdots & r_{2n} \\ r_{31} & r_{32} & r_{33} & \cdots & r_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & r_{m3} & \cdots & r_{mn} \end{bmatrix}$$

Aggregated weighted intuitionistic fuzzy decision matrix can be found by multiplying the matrix of aggregated intuitionistic fuzzy decision and the matrix of weights of attributes. For this multiplication, the following operation in Eq. 7 given in definition 4 (v) is used;

$$R \otimes W = \tilde{r}_{ij} = \begin{pmatrix} \mu_{A_{ij}} . \mu_j , \nu_{Aij} + \nu_j - \nu_{Aij} . \nu_j , \\ 1 - \nu_{A_{ij}} - \nu_j - \mu_{A_{ij}} . \mu_j + \nu_{A_{ij}} . \nu_j \end{pmatrix} \quad (7)$$

where $w_j = (\mu_j, \nu_j, \pi_j)$ and $r_{ij} = \left(\mu_{A_{ij}}, \nu_{A_{ij}}, \pi_{A_{ij}}\right)$. The aggregated weighted intuitionistic fuzzy decision matrix is as follows:

$$\tilde{R} = \left[\tilde{r}_{ij}\right]_{mxn} = \begin{bmatrix} \tilde{r}_{11} & \tilde{r}_{12} & \tilde{r}_{13} & \cdots & \tilde{r}_{1j} \\ \tilde{r}_{21} & \tilde{r}_{22} & \tilde{r}_{23} & \cdots & \tilde{r}_{2j} \\ \tilde{r}_{31} & \tilde{r}_{32} & \tilde{r}_{33} & \cdots & \tilde{r}_{3j} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \tilde{r}_{i1} & \tilde{r}_{i2} & \tilde{r}_{i3} & \cdots & \tilde{r}_{ij} \end{bmatrix}_{mxn}$$

and each element of this matrix which is is as follows:
$\tilde{r}_{ij} = (\tilde{\mu}_{A_{ij}W}, \tilde{\nu}_{A_{ij}W}, \tilde{\pi}_{A_{ij}W})$.

Step 7: Determine ideal solutions.

Let ϖ_1 be benefit criteria and ϖ_2 be cost criteria, respectively. ϕ^- is intuitionistic fuzzy negative-ideal solution and ϕ^+ intuitionistic fuzzy positive-ideal solution. Then ϕ^- and ϕ^+ are attained as:

$$\phi^- = \left(\mu_{\phi_j^- W}, \nu_{\phi_j^- W}, \pi_{\phi_j^- W}\right) \quad (8)$$

$$\phi^+ = \left(\mu_{\phi_j^+ W}, \nu_{\phi_j^+ W}, \pi_{\phi_j^+ W}\right) \quad (9)$$

$$\mu_{\phi_j^+ W} = \left(\left(\max_i \mu_{\phi_{ij} W} \mid j \in \varpi_1\right), \left(\min_i \mu_{\phi_{ij} W} \mid j \in \varpi_2\right)\right) \quad (10)$$

$$\nu_{\phi_j^+ W} = \left(\left(\min_i \nu_{\phi_{ij} W} \mid j \in \varpi_1\right), \left(\max_i \nu_{\phi_{ij} W} \mid j \in \varpi_2\right)\right) \quad (11)$$

$$\mu_{\phi_j^- W} = \left(\left(\min_i \mu_{\phi_{ij} W} \mid j \in \varpi_1\right), \left(\max_i \mu_{\phi_{ij} W} \mid j \in \varpi_2\right)\right) \quad (12)$$

$$\nu_{\phi_j^- W} = \left(\left(\max_i \nu_{\phi_{ij} W} \mid j \in \varpi_1\right), \left(\min_i \nu_{\phi_{ij} W} \mid j \in \varpi_2\right)\right) \quad (13)$$

Step 8: Calculate the distance measures.

The distances between candidates are measured on IFS. Different methods can be used to measure these distances. In this study, Euclidean distance was used which has been developed by Szmidt & Kacprzyk (2000). The positive distance measure d_i^+ and negative distance measure d_i^- of each candidate from intuitionistic fuzzy negative-ideal solution and intuitionistic fuzzy positive-ideal solution are calculated:

$$d_i^+ = \left\{ \frac{1}{2n} \sum_{j=1}^{n} \left[\begin{array}{l} \left(\mu_{\varphi_{ij} W} - \mu_{\varphi_j^+ W}\right)^2 + \left(\nu_{\varphi_{ij} W} - \nu_{\varphi_j^+ W}\right)^2 \\ + \left(\pi_{\varphi_{ij} W} - \pi_{\varphi_j^+ W}\right)^2 \end{array} \right] \right\}^{1/2} \quad (14)$$

$$d_i^- = \left\{ \frac{1}{2n} \sum_{j=1}^{n} \left[\begin{array}{l} \left(\mu_{\varphi_{ij} W} - \mu_{\varphi_j^- W}\right)^2 + \left(\nu_{\varphi_{ij} W} - \nu_{\varphi_j^- W}\right)^2 + \\ \left(\pi_{\varphi_{ij} W} - \pi_{\varphi_j^- W}\right)^2 \end{array} \right] \right\}^{1/2} \quad (15)$$

Step 9: Calculate the closeness coefficient of each candidate and rank the candidates with respect to their closeness coefficient.

The closeness coefficient of i^{th} candidate, x_i^*, is calculated by using the intuitionistic fuzzy positive-ideal solution d_i^+ and intuitionistic fuzzy negative-ideal solution d_i^- as follows:

$$x_i^* = \frac{d_i^-}{d_i^+ + d_i^-} \;, \quad 0 \le x_i^* \le 1 \quad (16)$$

The candidates are sequenced according to decreasing order of x_i^*'s.

Step 10: Select the candidate with the highest closeness coefficient. The candidate with the highest closeness coefficient is selected as the most appropriate personnel.

5. Case study

Step 1: Define personnel selection problem.
A company that manufactures batteries for vehicles was established in central Turkey more than 30 years ago. The company has production area of 40 thousand square meters. It provides employment fields, more than 400 experts, who

are young and dynamic people and about 75 of whom are administrative personnel.

The company, which is a supplier of automotive factories in France, Italy, South Korea and so on, tries to disseminate the identity of global supplier of automotive industry. For this reason, it targets to go to the forefront of global competition in the production of Li-Ion battery for electric vehicles. In this point, it would like to select the director of system analysis and design department that will work for this target.

Step 2: Apply of Delphi Technique.

Ten experts, who are working in various positions in the company, were determined for the application of the Delphi technique. The contact with experts was provided by e-mail.

Step 2.1. First of all, personnel selection problem of the company was defined to experts. Experts were asked to answer the following open-ended questions.

- Which attributes should be taken into consideration for selecting the director of system analysis and design department?
- Who may be decision makers to select the personnel for this position?

Step 2.1.1. Experts' judgments were summarized as in Table 1 and they were given feedback.

Table 1. Summary of experts' judgments at iteration 1

Attributes	Frequency	Decision Makers	Frequency
Leadership	9	A	8
Motivation	7	B	2
Work Experience	6	C	9
Proficiency	2	D	3
Appearance	3	E	7
Creativity	8	F	4
Age	6	G	3
Foreign Language	3	H	4
Computer Skills	1		
Graduate Degree	2		
Communication Skills	8		
Technical Knowledge	3		

Step 2.1.2. They were asked whether they will modify their judgments or not. Some of them modified their judgments. According to the responses received, the consensus was reached for six attributes (Leadership, Motivation, Work Experience, Creativity, Age, Communication Skills) and three decision makers (A, C, E).

Step 2.2. Experts were asked to answer the following question for the determined decision makers.

- Evaluate the determined decision makers for each attribute using linguistic terms in Table 2.

Table 2. Linguistic terms and IFNs

Linguistic terms	IFN
Very Important (VI)	(0.90, 0.10, 0.00)
Important (I)	(0.75, 0.20, 0.05)
Medium (M)	(0.50, 0.45, 0.05)
Unimportant (UI)	(0.35, 0.60, 0.05)
Very Unimportant (VUI)	(0.10, 0.90, 0.00)

Step 2.2.1. The evaluation received from experts was summarized in Table 3 and they were given feedback.

Table 3. Summary of experts' evaluations (frequency) at iteration 2

Attributes / Decision Makers	A	C	E
Leadership	VI(7), I(2), M(1)	VI(1), I(5), M(2), UI(1), VUI(1)	I(1), M(2), UI(5), VUI(2)
Motivation	VI(5), I(3), M(1), VUI(1)	VI(2), I(6), M(1), UI(1)	VI(1), I(1), M(5), UI(2), VUI(1)
Work Experience	VI(1), I(6), M(3)	VI(7), I(3)	I(2), M(1), UI(5), VUI(2)
Creativity	VI(2), I(5), M(1), UI(1), VUI(1)	VI(6), I(3), M(1)	VI(1), I(3), M(5), UI(1)
Age	VI(2), I(1), M(5), UI(1), VUI(1)	I(2), M(6), UI(2)	VI(3), I(5), M(2)
Communication Skills	I(2), M(7), VUI(1)	VI(2), I(5), M(2), UI(1)	VI(2), I(8)

Step 2.2.2. They were asked whether they will modify their evaluation or not. Some of them modified their evaluation. According to the responses received, the consensus was reached and was presented in Table 4.

Step 3: Define attributes, decision makers and calculate the weights of decision makers for each attribute. As a result of implementation of the Delphi technique, decision makers and attributes to be used for the personnel selection were obtained as follows:

Attributes are a_1: Leadership, a_2: Motivation, a_3: Work Experience, a_4: Creativity, a_5: Age, a_6: Communication Skills. Decision makers are δ_1: A, δ_2: C, δ_3: E.

According to their degree of importance in Table 4, the weights of decision makers for each attribute were calculated using Eq. 4 and were presented in Table 4.

Table 4. Importance and weights for decision makers

Attributes (j)	Decision Makers					
	δ_1	w_{j1}	δ_2	w_{j2}	δ_3	w_{j3}
	importance	weight	importance	weight	importance	weight
a_1	VI	0.437	I	0.384	UI	0.179
a_2	VI	0.406	I	0.356	M	0.238
a_3	I	0.441	VI	0.503	VUI	0.056
a_4	I	0.356	VI	0.406	M	0.238
a_5	UI	0.269	VUI	0.073	VI	0.658
a_6	VI	0.406	M	0.238	I	0.356

Step 4: Determine the weights of attributes by decision makers.

Decision makers evaluated attributes using linguistic terms in Table 2. Importance of attributes is shown in Table 5.

Table 5. Importance of attributes

j	Decision Makers δ_1	δ_2	δ_3
a_1	VI	VI	I
a_2	I	I	VI
a_3	I	M	I
a_4	VI	I	M
a_5	UI	M	VI
a_6	M	M	VI

Weights of attributes were calculated by using Eq.5 as follows:

$$W = \begin{bmatrix} (0.882, 0.113, 0.005) \\ (0.799, 0.170, 0.031) \\ (0.646, 0.301, 0.054) \\ (0.787, 0.189, 0.023) \\ (0.814, 0.181, 0.005) \\ (0.718, 0.263, 0.018) \end{bmatrix}^T$$

Step 5: Evaluate candidates by decision makers.

Decision makers evaluated candidates for six attributes using linguistic terms given in Table 6. These evaluations are shown in Table 7.

Table 6. Linguistic terms and IFNs

Linguistic terms	IFN
Extremely Good (EG)	(1.00, 0.00, 0.00)
Very Very Good (VVG)	(0.95, 0.05, 0.00)
Very Good (VG)	(0.85, 0.10, 0.05)
Good (G)	(0.70, 0.20, 0.10)
Medium (M)	(0.50, 0.35, 0.15)
Bad (B)	(0.35, 0.55, 0.10)
Very Bad (VB)	(0.25, 0.70, 0.05)
Very Very Bad (VVB)	(0.10, 0.90, 0.00)

Table 7. Evaluations for candidates

Attributes	Candidates	Decision Makers δ_1	δ_2	δ_3
a_1	x_1	VG	G	VG
	x_2	VVG	VG	G
	x_3	B	G	G
a_2	x_1	G	VG	VG
	x_2	VG	VG	G
	x_3	VG	G	VG
a_3	x_1	VG	M	VG
	x_2	VVG	M	G
	x_3	G	B	VVG
a_4	x_1	VG	G	M
	x_2	VVG	G	G
	x_3	G	M	VG
a_5	x_1	VG	G	B
	x_2	VVG	G	VG
	x_3	VVB	VG	G
a_6	x_1	VG	M	G
	x_2	VVG	VG	VG
	x_3	VVB	M	B

Step 6: Construct aggregated weighted intuitionistic fuzzy decision matrix.

Aggregated intuitionistic fuzzy decision matrix was calculated using Eq. 6 with respect to evaluations of decision makers.

$$R=\begin{bmatrix}(0.80,0.13,0.07) & (0.80,0.13,0.07) & (0.73,0.19,0.09) & (0.74,0.18,0.08) & (0.59,0.32,0.09) & (0.74,0.17,0.08)\\(0.90,0.08,0.02) & (0.82,0.12,0.06) & (0.82,0.14,0.03) & (0.84,0.12,0.04) & (0.88,0.09,0.03) & (0.90,0.08,0.02)\\(0.58,0.31,0.11) & (0.81,0.13,0.06) & (0.60,0.31,0.09) & (0.69,0.21,0.10) & (0.62,0.28,0.10) & (0.30,0.60,0.09)\end{bmatrix}$$

Aggregated weighted intuitionistic fuzzy decision matrix was calculated by multiplying R and W using Eq.7 as below:

$$\tilde{R}=\begin{bmatrix}(0.71,0.23,0.06) & (0.64,0.28,0.08) & (0.47,0.43,0.10) & (0.58,0.33,0.09) & (0.48,0.45,0.07) & (0.54,0.39,0.07)\\(0.79,0.19,0.02) & (0.66,0.27,0.07) & (0.53,0.40,0.07) & (0.66,0.29,0.05) & (0.72,0.25,0.03) & (0.65,0.32,0.03)\\(0.51,0.39,0.10) & (0.65,0.28,0.07) & (0.39,0.51,0.10) & (0.54,0.36,0.10) & (0.50,0.42,0.08) & (0.22,0.71,0.07)\end{bmatrix}$$

Step 7: Determine ideal solutions.

Age is considered as cost attribute and the other attributes are considered as benefit attributes. Intuitionistic fuzzy positive-ideal solution and intuitionistic fuzzy negative-ideal solution were determined by utilizing Eq. 8-13.

$$\varphi^{+}=\begin{bmatrix}(0.79,0.19,0.020) & (0.66,0.27,0.07) & (0.53,0.40,0.07)\\(0.66,0.29,0.05) & (0.48,0.45,0.07) & (0.54,0.39,0.07)\end{bmatrix}$$

$$\varphi^{+}=\begin{bmatrix}(0.51,0.39,0.10) & (0.64,0.28,0.08) & (0.39,0.51,0.10)\\(0.54,0.36,0.10) & (0.72,0.25,0.03) & (0.22,0.71,0.08)\end{bmatrix}$$

Step 8: Calculate distance measures.

By using Eq. 14 and 15, positive and negative distance measures for candidates were calculated as follows:

d_1^{+} = 0.062, d_2^{+} = 0.090, d_3^{+} = 0.209
d_1^{-} = 0.178, d_2^{-} = 0.209, d_3^{-} = 0.080

Step 9: Calculate the closeness coefficient of each candidate and rank the candidates with respect to their closeness coefficient.

The closeness coefficients of the candidates were calculated by Eq. 16 as follows:

x_1^{*} = 0.741, x_2^{*} = 0.698, x_3^{*} = 0.276

According to the closeness coefficients, candidates are ranked as $x_1 > x_2 > x_3$.

Step 10: Select the candidate with the highest closeness coefficient as the most appropriate personnel. First candidate was selected as the most appropriate personnel and should be assigned to the position as the director of system analysis and design department.

5.1. Sensitivity analysis

Assume that the weights of decision makers for each attribute are equivalent ($\delta_{j1}=\delta_{j2}=\delta_{j3}$). When the steps of the proposed method are applied again, distance measures and closeness coefficients of the candidates are shown in Table 8.

Table 8. Distance measures and closeness coefficients of the candidates

Candidates	d_i^{+}	d_i^{-}	x_i^{*}
x_1	0.060	0.134	0.693
x_2	0.054	0.176	0.766
x_3	0.176	0.054	0.235

Bali, Ö., Gümüş, S., Dağdeviren, M.(2013). A Group MADM Method for Personnel Selection Problem Using Delphi Technique Based on Intuitionistic Fuzzy Sets, Journal of Military and Information Science, 1(1), 1-13

Table 8 shows that ranking of the candidates were changed. Accordingly, the new ranking was $x_2 > x_1 > x_3$. Second one should be selected among the candidates.

In the case study, if the weights of decision makers for each attribute are equivalent, second candidate should be selected. However, if the weights of decision makers for each attribute are calculated separately, first candidate should be selected. As seen, the selected candidate is different. As it is understood, considering the weights of decision makers for each attribute affect the result of the process of the personnel selection.

6. Conclusion

In this study, a group MADM method in sensitivity of experts was developed for PS problem that consists of vagueness and imprecision. In many group decision making problems such as PS, decision makers' experience, position through the organization, effectiveness in the group and field of expertise for each attribute may affect the result of decision making process. Therefore, in this study, we assumed that the weights of decision makers are different for each attribute in PS problem. Delphi Technique was utilized to determine attributes and decision makers required for PS problem. Moreover, this technique was used to calculate the weights of decision makers for each attribute that how these weights are founded isn't clear in many MADM studies. Owing to the fact that evaluations of experts and decision makers show vagueness and imprecision, IFS was used to eliminate this issue. The developed group MADM method for PS was applied to PS problem as a case study. According to the results of the case study, the sequencing of candidates and also selected candidate as the most appropriate personnel for our proposed method with the weights of decision makers for each attribute is different from the method with no weights of decision makers. Hence, if experience, position through the organization, effectiveness in the group and profession of the decision makers are different and important, the weights of decision makers for each attribute should be taken into consideration in problems such as personnel selection. Considering that the group members to interact with other group members, it is beneficial to assess calculating the weights and importance of the decision makers for each attribute.

References

Atanassov, K. T. (1986). Intuitionistic fuzzy sets. Fuzzy Sets and Systems, 20, 87–96.

Atanassov, K. T. (1999). Intuitionistic fuzzy sets. Heidelberg: Springer.

Atanassov, K., Pasi, G. & Yager, R.R. (2005). Intuitionistic fuzzy interpretations of multi-criteria multi-person and multi-measurement tool decision making. International Journal of Systems Science, 36 (14), 859–868.

Boran, F.E., Genç, S. Genç, Kurt, M. & Akay, D. (2009). A multi-criteria intuitionistic fuzzy group decision making for supplier selection with TOPSIS method. Expert Systems with Applications, 36, 11363–11368.

Chang, C., Wu, C., Lin, C. & Chen, H. (2007). An application of AHP and sensitivity analysis for selecting the best slicing machine. Computers & Industrial Engineering, 52, 296–307.

Chen, C.T. (2000). Extension of the TOPSIS for group decision making under fuzzy environments, Fuzzy Sets and System. 114, 1–9.

Chen, S.M. & Tan, J. M. (1994). Handling multi criteria fuzzy decision-making problems based on vague set theory. Fuzzy Sets and Systems, 67, 163–172.

Chen, L.S. & Cheng, C.H. (2005). Selecting IS personnel use fuzzy GDSS based on metric distance method. European Journal of Operation Research, 160, 803–820.

Chien, C. & Chen, L. (2008). Data mining to improve personnel selection and enhance human capital: A case study in high-technology industry. Expert Systems with Applications, 34, 280–290.

Dağdeviren, M.. (2010). A hybrid multi-criteria decision-making model for personnel selection in manufacturing systems. Journal of Intelligent Manufacturing, 21(4), 451-460.

Dalkey, N. C. & Helmer, O. (1963). An experimental application of the Delphi method to the use of experts. Management Science, 9, 458–467.

Dursun, M. & Karsak, E.E. (2010). A fuzzy MCDM approach for personnel selection. Expert Systems with Applications, 37, 4324–4330.

Gerdsri, N. & Kocaoglu, D.F. (2007). Applying the Analytic Hierarchy Process (AHP) to build a strategic framework for technology roadmapping. Mathematical and Computer Modelling, 46, 1071–1080.

Göleç, A. & Kahya, E. (2007). A fuzzy model for competency-based employee evaluation and selection. Computers & Industrial Engineering, 52, 143–161.

Güngör, Z., Serhadlıoğlu, G. & Kesen, S.E. (2009). A fuzzy AHP approach to personnel selection problem. Applied Soft Computing, 9, 641–646.

Handfield, R., Walton, S.V., Sroufe, R. & Melnyk, S.A. (2002). Applying environmental criteria to supplier assessment: a study in the application of the Analytical Hierarchy Process. European Journal of Operational Research, 141, 70–87.

Hong, D.H. & Choi, C.H. (2000). Multi criteria fuzzy decision-making problems based on vague set theory. Fuzzy Sets and Systems, 114, 103–113.

Huang, D.K., Chiu, H.N., Yeh, R.H. & Chang, J.H. (2009). A fuzzy multi-criteria decision making approach for solving a bi-objective personnel assignment problem. Computers & Industrial Engineering, 56, 1–10.

Jahanshahlo, G.R., Hosseinzade, L.F. & Izadikhah, M. (2006a). An algorithmic method to extend TOPSIS for decision making problems with interval data. Applied Mathematics and Computation, 175, 1375–1384.

Jahanshahlo, G.R., Hosseinzade, L. F. & Izadikhah, M. (2006b). Extension of the TOPSIS method for decision making problems with fuzzy data. Applied Mathematics and Computation, 81, 1544–1551.

Jessop, A. (2004). Minimally biased weight determination in personnel selection. European Journal of Operation Research, 153, 433–444.

Karsak, E.E. (2001). Personnel selection using a fuzzy MCDM approach based on ideal and anti-ideal solutions. Lecture Notes in Economics and Mathematical Systems, 507, 393–402.

Kelemenis, A. & Askounis, D. (2010). A new TOPSIS-based multi-criteria approach to personnel selection. Expert Systems with Applications, 37, 4999–5008.

Lazarevic, S.P. (2001). Personnel selection fuzzy model, International Transactions in Operational Research. 8, 89–105.

Li, D-F. (2007). A fuzzy proximity approach to fuzzy multi-attribute decision making. Fuzzy Optimization and Decision Making, 6 (3) 237-254.

Liang, G-S. & Wang, M-J.J. (1994). Personnel selection using fuzzy MCDM algorithm. European Journal of Operational Research, 78 (1) 22-33.

Lin, H.-T. (2010). Personnel selection using analytic network process and fuzzy data envelopment analysis approaches. Computers & Industrial Engineering, 59, 937–944.

Liu, H.W. & Wang, W.G. (2007). Multi-criteria decision-making methods based on intuitionistic fuzzy sets. European Journal of Operational Research, 179, 220–233.

Liu, L., Huan, Y.X. and Xia, Z.Q. (2007). Multicriteria fuzzy decision-making methods based on intuitionistic fuzzy sets. Journal of Computer and System Sciences, 73, 84–88.

Malinowski, J., Weitzel, T. & Keim, T. (2008). Decision support for team staffing: An automated relational recommendation approach. Decision Support Systems, 45, 429–447.

Shen, Y.-C., Chang, S.-H., Lin, G.T.R. & Yu, H.-C. (2010). A hybrid selection model for emerging technology. Technological Forecasting & Social Change, 77, 151–166.

Szmidt, E. & Kacprzyk, J. (2000). Distances between intuitionistic fuzzy sets. Fuzzy Sets and Systems, 114, 505–518.

Szmidt, E. & Kacprzyk, J. (2002). Using intuitionistic fuzzy sets in group decision making. Control and Cybernetics, 31, 1037–1053.

Szmidt E. & Kacprzyk, J. (2003). A consensus-reaching process under intuitionistic fuzzy preference relations. International Journal of Intelligent Systems, 18, 837–852.

Tavana, M., Pirdashti, M., Kennedy, D.T., Belaud, J.-P. & Behzadian, M. (2012). A hybrid Delphi-SWOT paradigm for oil and gas pipeline strategic planning in Caspian Sea basin. Energy Policy, 40, 345–360.

Triantaphyllou, E. & Lin, C.T. (1996). Development and evaluation of five fuzzy multi attribute decision-making methods. International Journal of Approximate Reasoning, 14, 281–310.

Xu, Z.S. (2007a). Intuitionistic preference relations and their application in group decision making. Information Sciences, 177, 2363–2379.

Xu, Z.S. (2007b). Models for multiple attribute decision making with intuitionistic fuzzy information. International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems, 15, 285–297.

Xu, Z.S. (2007c). Intuitionistic fuzzy aggregation operators. IEE Transaction of Fuzzy Systems, 15 (6), 1179–1187.

Xu, Z. & Cai, X. (2010). Recent advances in intuitionistic fuzzy information aggregation. Fuzzy Optimization and Decision Making, 9 (4), 359-381.

Wang, P. (2009). QoS-aware web services selection with intuitionistic fuzzy set under consumer's vague perception. Expert Systems with Applications, 36 (3), 4460–4466.

Zhang, S. & Liu, S. (2011). A GRA-based intuitionistic fuzzy multi-criteria group decision making method for personnel selection. Expert Systems with Applications, 38, 11401–11405.