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A Fuzzy Model for Multi-Criteria

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Abstract. Selecting the best technician highly affects the stability and economy of industrial firms. Evaluating technician's suitability for a job is an important tool for Human Resources Managers (HRMs) to select the better candidates under various evaluation criteria. This paper introduces a fuzzy model in decision competition making for selecting the best technician in any firm or organization. Selected technician must fulfill the machining as well as the human requirement skills. Many of these attributes are of high level of vagueness and imprecision especially in concern with the human psychology. Due to the lack of complete information, uncertainty, and a high level of vagueness and imprecision for technician ranking in any opportunity, a technique to perform selection calculations on imprecise representations of parameters is presented. In this paper, linguistic terms and triangular fuzzy numbers describe decision-makers' opinions. A new algorithm is developed based on fuzzy measures to deal with such types of ranking problems. An illustrative example is given to demonstrate the procedure of the proposed methodology. Calculations based on fuzzy weighted average are performed to produce the ratings among selected technician alternatives. A model is conducted for linguistic evaluation for technicians' skill suitability measures values for different technician alternatives. Two techniques were used in this work for ranking the proposed alternatives; the preference relation using the α-cut, and the fuzzy mean and spread using probability distribution. In general, this method provides accurate selection and can be used easily in industry.

Keywords: Multi-criteria decision making, technicians ranking, Fuzzy logic, Fuzzy sets, α-cut threshold level, Fuzzy mean, Fuzzy spread.

1. Introduction

Hiring or rearranging staff for special vacancies presents a crucial decision due to the fact that the survival of the whole enterprise can depend upon the appropriate selection process. With high level of business competition, it is vital to have flexible staffs that are able to adapt themselves with work circumstances. Thus, the most suitable choice of the personnel has a greater influence over the company's future development[1].

In general, the staff selection problem is very difficult to be solved, even when it is tackled in a simplified version containing only a single criterion and a homogeneous skill[2]. When multiple criteria and various skills are involved, the problem becomes much more difficult. So, it will be hard, if not impossible, to apply used mathematical techniques or traditional programming to solve the problem. In most cases of staff selection problems, the information that is available could not be precise or exact. Even more, the imprecise information could be represented as linguistic information in terms of variables such as opinions, thoughts, feelings, believes, etc. These variables refer to professional knowledge, leadership, sense of responsibility, relationships and cooperation with the other team members in the work group[3].

2. Literature Review

In most real-world problems, some of the decision data can be precisely assessed while others cannot. Crisp numbers are used to represent data which can be precisely measured. For those data which cannot be precisely assessed, fuzzy numbers can be used to denote them. The use of fuzzy numbers allows us to incorporate unquantifiable information, incomplete information, non-obtainable information and partially ignorant facts into the decision model. When decision data are precisely known, they should not be forced into a fuzzy format in the decision analysis.

In general, many concepts, tool and techniques of artificial intelligence, in particular in the field of knowledge representation and reasoning, can be used to improve human consistency and implementability of numerous models and tools in broadly perceived decision making and operations research. Kahraman *et al.*[4] compared catering firms using Fuzzy Analytic Hierarchy Process (FAHP) multi-attribute decision-making method for selecting the best among a set of alternatives. FAHP is extensively applied, especially in large-scale problems where many criteria must be considered and where the evaluation of alternatives is mostly subjective[5]. Kahraman *et al.*[6] concluded that FAHP is only based on fuzzy subjective attribute weights and has many computational steps and is the most complex one. On the other hand, Wang *et al.* [7] showed by examples that the priority vectors determined by the extent analysis method do not represent the relative importance of decision criteria or alternatives and that the misapplication of the extent analysis method to FAHP problems may lead to a wrong decision to be made and some useful decision information such as decision criteria and fuzzy comparison matrices not to be considered.

Sen and Çınar[8] used AHP and max–min approach combined fuzzy for the evaluation and pre-allocation of operators with multiple skills. They concluded that their methodology enabled the decision makers to simultaneously examine the strengths and weaknesses of the operators by comparing them with related qualitative and quantitative criteria. They added that their methodology also incorporates relative weights of these criteria into the evaluation process. Wu[9] used grey related analysis and Dempster–Shafer theory for Supplier selection. He stated that the proposed approach uses both quantitative and qualitative data and provides alternative tools to evaluate and improve supplier selection decisions in an uncertain global market. He concluded that the proposed approach is applied to a complex international supplier selection problem with both quantitative and qualitative data. Sanayei et al. [10] stated that Supplier selection is a complex multi-criteria problem including both quantitative and qualitative factors. They proposed an integrated approach of multi-attribute utility theory (MAUT) and linear programming (LP) for rating and choosing the best suppliers and defining the optimum order quantities among selected ones in order to maximize total additive utility.

Wang *et al.* [11] proposed Fuzzy hierarchical TOPSIS for supplier selection. They found that TOPSIS which not only is well suited for evaluating fuzziness and uncertainty problems, but also can provide more objective and accurate criterion weights. Wu *et al.* [12] presented an integrated multi-objective decision-making process by using analytic network process (ANP) and mixed integer programming (MIP) to optimize the selection of supplier. They found that when a hypothetical example is presented and the results indicated that the combination of analytic network process (ANP) and mixed integer programming (MIP) provided useful tool to select the optimal supplier.

Aouam *et al*.[13] stated that Multi-attribute decision making forms an important part of the decision process for both the small (an individual) and the large (an organiztion) problems. They concluded that the fuzzy ranking method used can considerably influence the results. Devedzic and Pap[14] used multicriteria-multistages linguistic evaluation and ranking of machine tools. They stated that a linguistic value generated this way contains a lot of information which can be used in further procedure of process planning. They concluded that the described procedure of decision making presents part of a much wider framework for selection of elements and parameters of metal cutting process planning. Jiang *et al*.[15] used fuzzy similarity-based rough set method for case-based reasoning and its application in tool selection. They introduced a new technique for feature weighting and reduction based on the fuzzy similarity based rough set theory. They proved that the proposed method is feasible. Shehab and Abdalla[16] developed manufacturing cost modelling for concurrent product development. They mentioned that to handle the uncertainty in cost estimation model that cannot be addressed by traditional analytical methods, a fuzzy logic-based knowledge representation is implemented in the developed system. They found that fuzzy logic-based knowledge representation is applied to deal with uncertainty in the knowledge of cost model. Vonderembse *et al*. [17] provided insights for discrete part manufacturing firms that design, implement, and participate in supply chains. It defines the characteristics for standard, innovative, and hybrid products, and it provides a framework for understanding lean and agile supply chains.

Ramadan[18] used a fuzzy model for research and development (R&D) project selection with multi-criteria decision making. He mentioned that the results of the proposed framework indicate that the proposed technique can handle multigoals' problems effectively. He added that the presented framework proved its capability to select the most appropriate improvement project within a group of suggested alternatives even within unequal important attributed variables. Finally, he concluded that his proposed algorithm has the capability to deal with similar types of the same situations. Huang[19] proposes a practical tool of incorporating random fuzzy uncertainty into project selection. He concluded that though he discussed the project selection problem in a simple situation, he explored a new direction in this field which is random fuzzy project selection and more complicated cases will be new areas for further studies.

This research paid most attention to determine the suitable technician depends on many criteria (attributes) based on the firm's strategy. The quality of final allocation decision is largely dependent on the machining and human requirements skills. Most of the researchers do not consider both qualitative and quantitative criteria in their solutions. And hence, this paper fills this gap by presenting a methodology for facilitating the preallocation decisions like evaluating technician's performance based on both qualitative and quantitative criteria. Many of these attributes are of high level of vagueness and imprecise. A fuzzy multi-attribute with multi-expert approach for selecting the best qualified technician among others will be introduced; and the implementation process will be shown by an illustrative example. This method provides accurate selection and can be used easily in industry than other tools such as AHP method.

3. Basic Concepts of Fuzzy Numbers

A fuzzy set $\tilde{A}$ in a universe of discourse X is characterized by a membership function $\mu_{\tilde{A}}$ (x), which associates with each element x in X a real number in the interval [0, 1]. The function value $\mu_{\tilde{A}}$ (x) is termed the grade of membership of x in $\tilde{A}$. Special cases of fuzzy numbers include crisp real number and intervals of real numbers. Although there are many shapes of fuzzy numbers, the triangular and trapezoidal shapes are used most often for representing fuzzy numbers (For more details, see Lee, and Lee-Kwang[20]). The following descriptions and definitions show that membership function of the triangular fuzzy number, and its operations.

Definition 3.1. A triangular fuzzy number is defined as a triplet (a_1, a_2, a_3), as shown in Fig.1. Its membership function is defined as[18]:

$$\mu_{\tilde{A}} = \begin{cases} 0, & x < a_1 \\ (x - a_1)/(a_2 - a_1) & a_1 \le x \le a_2, \\ (a_3 - x)/(a_3 - a_2) & a_2 \le x \le a_3, \\ 0, & x > a_3 \end{cases} \tag{1}$$

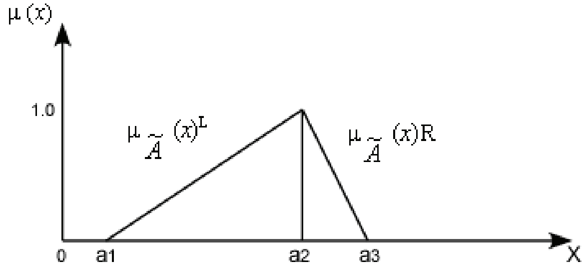

Fig. 1. The membership function $\mu_{\tilde{A}}$.

Let $\tilde{A}$ and $\tilde{B}$ be two fuzzy numbers parameterized by the triplet (a_1, a_2, a_3) and (b_1, b_2, b_3), respectively. Then the operations of triangular fuzzy numbers are expressed as:

$$
\begin{aligned}
\tilde{A} \oplus \tilde{B} &= (a_1, a_2, a_3) \oplus (b_1, b_2, b_3) = (a_1 + b_1, a_2 + b_3, a_3 + b_3),\\
\tilde{A} \ominus \tilde{B} &= (a_1, a_2, a_3) \ominus (b_1, b_2, b_3) = (a_1 - b_3, a_2 - b_2, a_3 - b_1),\\
\tilde{A} \otimes \tilde{B} &= (a_1, a_2, a_3) \otimes (b_1, b_2, b_3) = (a_1 \times b_1, a_2 \times b_2, a_3 \times b_3),\\
\tilde{A} \oslash \tilde{B} &= (a_1, a_2, a_3) \oslash (b_1, b_2, b_3) = (a_1 / b_3, a_2 / b_2, a_3 / b_1).
\end{aligned} \tag{2}
$$

Definition 3.2. A linguistic variable is a variable whose values are expressed in linguistic terms. For example, weight is a linguistic variable whose values are very low, low, medium, high, very high,… *etc*. Positive triangular Fuzzy numbers can represent these linguistic values[18].

Definition 3.3. For a fuzzy set $\tilde{A}$ defined on X and for any number $\alpha \in [0, 1]$; the α-cut, $\tilde{A}^{\alpha}$, and the strong α-cut, $\tilde{A}^{\alpha^+}$ are defined as[18]:

$$
\begin{aligned}
\tilde{A}^{\alpha} &= \{x \mid \mu_{\tilde{A}}(x) \geq \alpha\},\\
\tilde{A}^{\alpha^+} &= \{x \mid \mu_{\tilde{A}}(x) > \alpha\}.
\end{aligned} \tag{3}
$$

That is, the α-cut (or the strong α -cut) of a fuzzy set $\tilde{A}$ is the crisp set $\tilde{A}^{\alpha}$ (or the crisp set $\tilde{A}^{\alpha^+}$) that contains all the elements of the universal set X whose membership grades in $\tilde{A}$ are greater than or equal to (or only greater than) the specified value of α.

A level threshold ($0<\alpha<1$) of the fuzzy set is defined to show the decision-makers' confidence to their judgments. The definition of the triangular fuzzy number with the interval confidence at level α can be determined as follows:

$$M_\alpha = [(a_2 - a_1)\,\alpha + a_1, (a_2 - a_3)\,\alpha + a_3] \quad \forall\ \alpha \in [0, 1] \tag{4}$$

4. Algorithm and Methodology to Evaluate Technicians Skills

In the following, a methodology to deal with technician ranking problems is presented. The concept selection can be described as a problem of ranking *m* technicians (P_i; i = 1, 2, ..., *m*) by the decision maker. He/she wishes to select the technician which best satisfy the criteria from amongst *m* technicians, with the help of information about the technicians for each of *k* criteria (C_j; j = 1, 2,…., *n*) and also the relative importance of each criterion (W_j; j = 1, 2. …, *n*).

Step 1. Perform a decision-makers' committee of experts (DM_k; k=1, 2,…, l) and determine the technicians' alternatives (P_i; i= 1, 2, …, m) and the decision criteria (C_j; j=1, 2, …, n) to be evaluated.

Step 2. Determine the fuzzy rating and importance weight of the k-th decision maker. Hence, the aggregated fuzzy weights (W_j) of each criterion can be calculated as:

$$W_j = 1/k\ c\ (W_1 + W_2 + \ldots.. + W_{jk}),\ j = 1, 2, \ldots., n. \tag{5}$$

Step 3. Obtain the decision matrix by identifying the criteria values as crisp data, triangular fuzzy numbers or linguistic terms for each k-th decision maker. Then, the aggregated crisp data can be calculated as:

$$Xij = 1/k \sum_{k=1}^{l} x_{ijk} \tag{6}$$

However, the aggregated rating linguistic terms as well as for the aggregated rating of fuzzy numbers can be calculated as:

$$\begin{aligned} a_{ij} &= \min_k \{a_{ijk}\} \\ b_{ij} &= 1/k \sum_{k=1}^{l} b_{ijk} \\ cij &= \max_k \{cijk\}, \end{aligned} \tag{7}$$

Step 4. Normalize the decision matrix so that a linear criteria scales into unit-free and comparable. 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). Therefore, the normalized data can be computed as:

For crisp ratings, the normalized values for benefit-related criteria ($j=1,\ldots, n_1$) is expressed in Eq. (8) as well as for cost-related criteria ($j= n_1+1, \ldots, n_2$) can be expressed in Eq. (9). In case of benefit -related criterion only, Eq. (8) should be implemented.

$$r_{ij} = \left\{ \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \right\} \tag{8}$$

$$r_{ij} = \left\{ \frac{x_{ij}^{-1}}{\sum_{i=1}^{m} x_{ij}^{-1}} \right\} \tag{9}$$

For fuzzy ratings denoted by triangular fuzzy numbers as (a_{ij}, b_{ij}, c_{ij}), the normalized values for benefit-related criteria ($j= n_2+1, \ldots, n_3$) is expressed in Eq. (10) and cost-related criteria ($j= n_3+1, \ldots, n$) can be expressed in Eq. (11). In case of benefit -related criterion only, Eq. (10) should be implemented.

$$r_{ij} = \left\{ \frac{a_{ij}}{\sum_{i=1}^{m} c_{ij}}, \frac{b_{ij}}{\sum_{i=1}^{m} b_{ij}}, \frac{c_{ij}}{\sum_{i=1}^{m} a_{ij}} \right\} \tag{10}$$

$$r_{ij} = \left\{ \frac{c_{ij}^{-1}}{\sum_{i=1}^{m} a_{ij}^{-1}}, \frac{b_{ij}^{-1}}{\sum_{i=1}^{m} b_{ij}^{-1}}, \frac{a_{ij}^{-1}}{\sum_{i=1}^{m} c_{ij}^{-1}} \right\} \tag{11}$$

Step 5. Compute the weighted normalized decision matrix by multiplying the aggregate weights for each criterion by normalized criterion values. This can be expressed as in Eq. (12).

$$r_i = \sum_{j=1}^{n} w_j \otimes r_{ij} \tag{12}$$

Step 6. Determine the ordering value of each of the alternatives. Using Eq. (13) and Eq. (14), calculate the fuzzy distances of each alternative with the maximum distance ($\underset{\max i}{\overset{\alpha}{\mathrm{D}}}$, $\underset{\max i}{\overset{1}{\mathrm{D}}}$) and the minimum distance ($\underset{\max i}{\overset{\alpha}{\mathrm{D}}}$, $\underset{\max i}{\overset{1}{\mathrm{D}}}$) determine by Eq. (15) and Eq. (16). $\overset{\alpha}{\mathrm{D}}$ and $\overset{1}{\mathrm{D}}$ are the fuzzy distances under f (α) = α and f (α) = 1, respectively.

$$D^2 (\tilde{X}, M) = (b - M)^2 + 1/3\,(b - M)\,[(c + a) - 2b] + 1/18\,[(c-b)^2 + (b-a)^2] - 1/18[(c-b)(b-a)] \quad f(\alpha) \approx \alpha \qquad (13)$$

$$D^2 (\tilde{X}, M) = (b - M)^2 + 1/2\,(b - M)\,[(c + a) - 2b] + 1/9\,[(c-b)^2 + (b-a)^2] - 1/9[(c-b)(b-a)] \quad f(\alpha) \approx 1 \qquad (14)$$

Where M is either Max. or Min. and f (α) is a weighting function: f (α) ≈ α indicating more weights given to intervals at higher α level, and f (α) ≈ 1 representing equal weights for intervals at different levels of α.

The Max. and Min. are determined as follows:

$$\text{Max. (M)} \geq \sup \left[\underset{\max i}{\overset{\alpha}{\mathrm{D}}} \; s\left(\underset{i}{\tilde{P}}\right) \right] \qquad (15)$$

$$\text{Min. (M)} \leq \inf \left[\underset{\max i}{\overset{\alpha}{\mathrm{D}}} \; s\left(\underset{i}{\tilde{P}}\right) \right] \qquad (16)$$

Where $s\left(\underset{i}{\tilde{P}}\right)$ is the support of fuzzy numbers $\left(\underset{i}{\tilde{P}}\right)$, i =1, 2,…, m.

Step 7. Rank the alternatives with respect to their fuzzy distances. If $Dmax_p > Dmax_q$ and $Dmin_p < Dmin_q$; then, $r_p < r_q$, $p \neq q$, p = 1, 2, …, m; q = 1, 2, ….., m; and P_q is ranked earlier than P_p. If only one of two conditions is satisfied, a fuzzy number might be outranked the others depending upon context of the problem. Zhang *et al.* [21] have provided an example to show how different decision makers make decision under this condition.

5. Illustrative Example

A high technology company desires to select a suitable proposed qualified technician. After preliminary screening, seven technicians, P_1, P_2, P_3, P_4, P_5, P_6, and P_7 remain for further evaluation. A committee of three decision makers DM_1, DM_2, and DM_3 has been formed to select the most suitable technician. Twelve criteria are mainly considered as shown in Table 1. The technicians were evaluated by the decision makers' committee through observations and tests. Many of these attributes are of high level of vagueness and imprecise especially in concern with the human psychology.

Table 1. Fuzzy description of attributes based on machining and human requirements skills.

1	Turning Skills (C_1)	5	Endurance (C_5)	9	Physical Capability (C_9)
2	Milling Skills (C_2)	6	Stress Tolerance (C_6)	10	Moral Personality (C_{10})
3	Drilling Skills (C_3)	7	Works in a Team (C_7)	11	Biomechanical Capability (C_{11})
4	Grinding Skills (C_4)	8	Talent (C_8)	12	Experience (C_{12})

The assessment of the technician alternatives versus the twelve criteria is given using linguistic ratings (Extremely Poor, Very Poor, Poor, Medium Poor, Fair, Medium Good, Good, Very Good, and Extremely Good). Table 2 provides the data set used to rank technician. In the data set, EP, VP, P, MP, F, MG, G, VG, EG denote “Extremely Poor”, “Very Poor”, “Poor”, “Medium Poor”, “Fair”, “Medium Good”, “Good”, “Very Good”, Extremely Good”, respectively. The membership functions of the linguistic variables are demonstrated in Fig. 2.

The decision makers utilize the linguistic terms to identify the importance of the decision criteria, where EL, VL, L, ML, M, MH, H, VH, and EH denote “Extremely Low”, “Very Low”, “Low”, “Medium Low”, “Medium”, “Medium High”, “High”, “Very High”, and “Extremely High” importance, respectively. The weights assigned to the criteria by the three decision makers are given in Table 2. The membership functions of the importance weights are represented in the Fig. 3.

The aggregated fuzzy rating that are calculated by Eq. (7) and fuzzy weight of each criterion that are calculated using Eq. (5) are shown in Table 3. An example for calculating Table 3 for technician 1 and his Turning Skills is as follows:

Min. = (Min. G + Min. VG + Min. VG) / 3 = (0.6 + 0.7 + 0.7) / 3 = 0.67

Av. = (Av. G + Av. VG + Av. VG) / 3 = (0.7 + 0.8 + 0.8) / 3 = 0.77

Max. = (Max. G + Max. VG + Max. VG) / 3 = (0.8 + 0.9 + 0.9) / 3 = 0.87

Table 2. Data **used to assess the ranking of technician alternatives**.

Criterion		technician 1	technician 2	technician 3	technician 4	technician 5	technician 6	technician 7	Weight
Turning Skills	DM1	G	P	F	F	VG	MG	VP	H
	DM2DM	VG	MP	G	G	EG	F	MP	VH
		VG	P	MG	MG	EG	F	P	VH
Milling Skills	DM1	VP	EG	P	EP	G	VG	F	EH
	DM2	MP	VG	MP	P	MG	EG	F	M
	DM3	P	VG	F	MP	G	EG	MG	MH
Drilling Skills	DM1	G	VG	MG	MG	EG	EG	G	EH
	DM2	MG	VG	MG	MG	G	EG	G	H
	DM3	MG	G	MG	F	VG	VG	MG	VH
Grinding Skills	DM1	G	VG	F	F	EG	EG	EG	MH
	DM2	F	MG	F	F	G	G	EG	MH
	DM3	G	G	F	MG	G	G	VG	MH
Endurance	DM1	VG	MG	MG	VG	MG	G	VP	VH
	DM2	G	EG	MG	G	G	VG	F	H
	DM3	F	G	G	G	F	EG	MP	L
Stress Tolerance	DM1	G	MG	F	VG	F	G	P	H
	DM2	MG	EG	MP	MG	MP	VG	F	VH
	DM3	MG	G	G	VG	MG	VG	MP	MH
Works in a Team	DM1	G	MG	F	MG	G	VG	MP	EH
	DM2	MG	G	MP	G	F	VG	VP	VH
	DM3	F	G	G	VG	F	EG	P	M
Talent	DM1	F	MG	F	MG	VG	EG	VG	M
	DM2	VG	G	P	MG	G	VG	MG	VH
	DM3	G	G	F	MG	VG	VG	G	ML
Physical Capability	DM1	VG	G	F	MG	F	VG	F	VH
	DM2	MG	MG	EP	G	MP	VG	VP	EH
	DM3	F	VG	F	G	G	VG	MG	H
Moral Personality	DM1	F	VG	G	G	MG	G	F	H
	DM2	P	EG	G	VG	F	G	MP	EH
	DM3	MG	VG	G	VG	G	VG	MG	L
Biomecha-nical Capability	DM1	EP	G	VP	VG	F	VG	MP	VL
	DM2	VP	F	EP	G	P	MG	VP	H
	DM3	P	F	VP	VG	F	VG	G	M
Experience	DM1	G	G	G	MG	VG	G	MG	VH
	DM2	G	G	F	MP	EG	EG	MG	H
	DM3	VG	G	F	P	EG	VG	G	EH

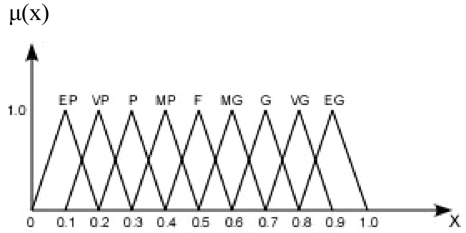

Fig. 2. Membership functions for linguistic variables.

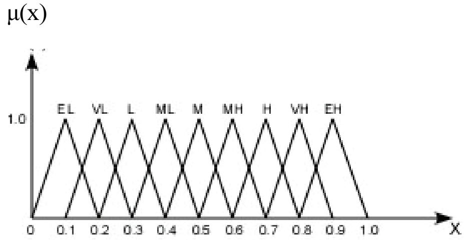

Fig. 3. Membership functions for importance weights.

Table 3. The aggregated fuzzy ratings and fuzzy weights.

Criterion		technician 1	technician 2	technician 3	technician 4	technician 5	technician 6	technician 7	Weight
Turning Skills	Min.	0.67	0.23	0.50	0.50	0.77	0.43	0.20	0.67
	Av.	0.77	0.33	0.60	0.60	0.87	0.53	0.30	0.77
	Max.	0.87	0.43	0.70	0.70	0.97	0.63	0.40	0.87
Milling Skills	Min.	0.20	0.73	0.30	0.17	0.57	0.77	0.43	0.57
	Av.	0.30	0.83	0.40	0.27	0.67	0.87	0.53	0.67
	Max.	0.40	0.93	0.50	0.37	0.77	0.97	0.63	0.77
Drilling Skills	Min.	0.53	0.67	0.50	0.47	0.70	0.77	0.57	0.70
	Av.	0.63	0.77	0.60	0.57	0.80	0.87	0.67	0.80
	Max.	0.73	0.87	0.70	0.67	0.90	0.97	0.77	0.90
Grinding Skills	Min.	0.53	0.60	0.40	0.43	0.67	0.67	0.77	0.50
	Av.	0.63	0.70	0.50	0.53	0.77	0.77	0.87	0.60
	Max.	0.73	0.80	0.60	0.63	0.87	0.87	0.97	0.70
Endurance	Min.	0.57	0.63	0.53	0.63	0.50	0.70	0.27	0.50
	Av.	0.67	0.73	0.63	0.73	0.60	0.80	0.37	0.60
	Max.	0.77	0.83	0.73	0.83	0.70	0.90	0.47	0.70
Stress Tolerance	Min.	0.53	0.63	0.43	0.63	0.40	0.67	0.30	0.60
	Av.	0.63	0.73	0.53	0.73	0.50	0.77	0.40	0.70
	Max.	0.73	0.83	0.63	0.83	0.60	0.87	0.50	0.80
Works in a Team	Min.	0.50	0.57	0.43	0.60	0.47	0.73	0.20	0.63
	Av.	0.60	0.67	0.53	0.70	0.57	0.83	0.30	0.73
	Max.	0.70	0.77	0.63	0.80	0.67	0.93	0.40	0.83
Talent	Min.	0.57	0.57	0.33	0.50	0.67	0.73	0.60	0.47
	Av.	0.67	0.67	0.43	0.60	0.77	0.83	0.70	0.57
	Max.	0.77	0.77	0.53	0.70	0.87	0.93	0.80	0.67
Physical Capability	Min.	0.53	0.60	0.27	0.57	0.43	0.70	0.33	0.70
	Av.	0.63	0.70	0.37	0.67	0.53	0.80	0.43	0.80
	Max.	0.73	0.80	0.47	0.77	0.63	0.90	0.53	0.90
Moral Personality	Min.	0.37	0.73	0.60	0.67	0.50	0.63	0.40	0.53
	Av.	0.47	0.83	0.70	0.77	0.60	0.73	0.50	0.63
	Max.	0.57	0.93	0.80	0.87	0.70	0.83	0.60	0.73
Biomechanical Capability	Min.	0.10	0.47	0.07	0.67	0.33	0.63	0.33	0.37
	Av.	0.20	0.57	0.17	0.77	0.43	0.73	0.43	0.47
	Max.	0.30	0.67	0.27	0.87	0.53	0.83	0.53	0.57
Experience	Min.	0.63	0.60	0.47	0.33	0.77	0.70	0.53	0.70
	Av.	0.73	0.70	0.57	0.43	0.87	0.80	0.63	0.80
	Max.	0.83	0.80	0.67	0.53	0.97	0.90	0.73	0.90

The criteria values for each technician are normalized using Eqs. (8-11). These normalized fuzzy ratings are shown in Table 4. An example for calculating Table 4 for technician 1 and his Turning Skills is as follows:

Table 4. The normalized fuzzy ratings and fuzzy weights.

Normalized		technician 1	technician 2	technician 3	technician 4	technician 5	technician 6	technician 7	Weight
Turning Skills	Min.	0.14	0.05	0.11	0.11	0.16	0.09	0.04	0.07
	Av.	0.19	0.08	0.15	0.15	0.22	0.13	0.08	0.09
	Max.	0.26	0.13	0.21	0.21	0.29	0.19	0.12	0.13
Milling Skills	Min.	0.04	0.16	0.07	0.04	0.12	0.17	0.09	0.06
	Av.	0.08	0.22	0.10	0.07	0.17	0.22	0.14	0.08
	Max.	0.13	0.29	0.16	0.12	0.24	0.31	0.20	0.11
Drilling Skills	Min.	0.10	0.12	0.09	0.08	0.13	0.14	0.10	0.08
	Av.	0.13	0.16	0.12	0.12	0.16	0.18	0.14	0.10
	Max.	0.17	0.21	0.17	0.16	0.21	0.23	0.18	0.13
Grinding Skills	Min.	0.10	0.11	0.07	0.08	0.12	0.12	0.14	0.05
	Av.	0.13	0.15	0.10	0.11	0.16	0.16	0.18	0.07
	Max.	0.18	0.20	0.15	0.16	0.21	0.21	0.24	0.10
Endurance	Min.	0.11	0.12	0.10	0.12	0.10	0.13	0.05	0.05
	Av.	0.15	0.16	0.14	0.16	0.13	0.18	0.08	0.07
	Max.	0.20	0.22	0.19	0.22	0.18	0.23	0.12	0.10
Stress Tolerance	Min.	0.11	0.13	0.09	0.13	0.08	0.13	0.06	0.06
	Av.	0.15	0.17	0.12	0.17	0.12	0.18	0.09	0.09
	Max.	0.20	0.23	0.18	0.23	0.17	0.24	0.14	0.12
Works in a Team	Min.	0.10	0.12	0.09	0.12	0.10	0.15	0.04	0.07
	Av.	0.14	0.16	0.13	0.17	0.13	0.20	0.07	0.09
	Max.	0.20	0.22	0.18	0.23	0.19	0.27	0.11	0.12
Talent	Min.	0.11	0.11	0.06	0.09	0.12	0.14	0.11	0.05
	Av.	0.14	0.14	0.09	0.13	0.16	0.18	0.15	0.07
	Max.	0.19	0.19	0.13	0.18	0.22	0.24	0.20	0.10
Physical Capability	Min.	0.11	0.12	0.06	0.12	0.09	0.14	0.07	0.08
	Av.	0.15	0.17	0.09	0.16	0.13	0.19	0.10	0.10
	Max.	0.21	0.23	0.14	0.22	0.18	0.26	0.16	0.13
Moral Personality	Min.	0.07	0.14	0.11	0.13	0.09	0.12	0.08	0.06
	Av.	0.10	0.18	0.15	0.17	0.13	0.16	0.11	0.08
	Max.	0.15	0.24	0.21	0.22	0.18	0.21	0.15	0.11
Biomechanical Capability	Min.	0.03	0.12	0.02	0.17	0.08	0.16	0.08	0.04
	Av.	0.06	0.17	0.05	0.23	0.13	0.22	0.13	0.06
	Max.	0.12	0.26	0.10	0.33	0.21	0.32	0.21	0.08
Experience	Min.	0.12	0.11	0.09	0.06	0.14	0.13	0.10	0.08
	Av.	0.15	0.15	0.12	0.09	0.18	0.17	0.13	0.10
	Max.	0.21	0.20	0.17	0.13	0.24	0.22	0.18	0.13

Min. = 0.67 / (sum of Max. Turning Skills for all operators)
= 0.67 / (0.87 + 0.43 + 0.7 + 0.7 + 0.97 + 0.63 + 0.4) = 0.14

Av. = 0.77 / (sum of Av. Turning Skills for all operators)
= 0.77 / (0.77 + 0.33 + 0.6 + 0.6 + 0.87 + 0.53 + 0.3) = 0.19

Max. = 0.87 / (sum of Min. Turning Skills for all operators)
= 0.87 / (0.67 + 0.23 + 0.5 + 0.5 + 0.77 + 0.43 + 0.2) = 0.26

The transformation values of fuzzy weights of the twelve criteria are computed for each technician using Eq. (12) as shown below for the first technician:

$$r_1 = (.14, .19, .26) \otimes (.07, .09, .13) \oplus (.04, .08, .13) \otimes (.06, .08, .11) \oplus (.10, .13, .17)$$

$$\otimes (.08, .10, .13) \oplus (.10, .13, .18) \otimes (.05, .07, .10) \oplus (.11, .15, .20) \otimes (.05, .07, .10) \oplus (.11, .15, .20)$$

$$\otimes (.06, .09, .12) \oplus (.10, .14, .20) \otimes (.07, .09, .12) \oplus (.11, .14, .19) \otimes (.05, .07, .10)$$

$$\oplus (.11, .15, .21) \otimes (.08, .10, .13) \oplus (.07, .10, .15) \otimes (.06, .08, .11) \oplus (.03, .06, .12)$$

$$\otimes (.04, .06, .08) \oplus (.12, .15, .21) \otimes (.08, .10, .13)$$

Then, the fuzzy values for each technician are obtained as shown in Table 5.

Table 5. The fuzzy rating values.

	r 1	r2	r3	r4	r5	r6	r7
a	0.07	0.09	0.06	0.08	0.08	0.10	0.06
b	0.13	0.16	0.12	0.14	0.15	0.18	0.12
c	0.25	0.29	0.22	0.27	0.29	0.33	0.22

From the previous matrix, let Max. (M) = 0.33 and Min. (M) = 0.06, the ordering values of all technicians can be obtained using Eq. (13) and Eq. (14). The results are tabulated in Table 6.

Table 6. The ordering values of all technicians.

		technician 1	technician 2	technician 3	technician 4	technician 5	technician 6	technician 7
f(α)≈α	$D^{\alpha}_{\max i}$	0.038767	0.031729	0.045435	0.036759	0.032713	0.026129	0.045852
	$D^{\alpha}_{\min i}$	0.011341	0.017199	0.007654	0.012951	0.016164	0.023956	0.00753
F (α)≈1	$D^{1}_{\max i}$	0.037333	0.030413	0.043927	0.035328	0.031379	0.024991	0.044329
	$D^{1}_{\min i}$	0.012396	0.018666	0.008438	0.014142	0.017556	0.025856	0.00831

From the above calculations, the ranking order can be obtained for all alternatives. When f (α) ≈ α , the technicians ranking order was P6, P2, P5, P4, P1, P3, and P7. When f (α) ≈ 1, the ranking order was also the same sequence. The decision, therefore, is to select technician 6, who is the best technician among the proposed ones.

Figure 4 shows the fuzzy triangular values for each technician. The most technician alternative to the right is technician 6. This ensures the last decision depending on the ranking order results from the proposed technique.

Figures 5 and 6 show the technicians' ascending and descending fuzzy values at different α-Cut. It is clear that technician 6 has the higher fuzzy values for all α-Cut.

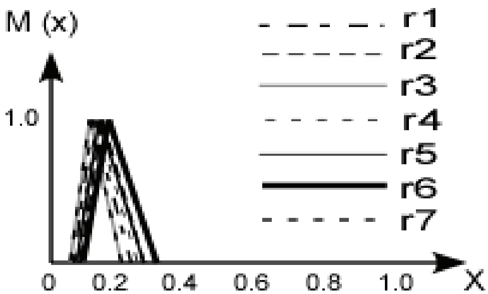

Fig. 4. The fuzzy triangular values for each technician.

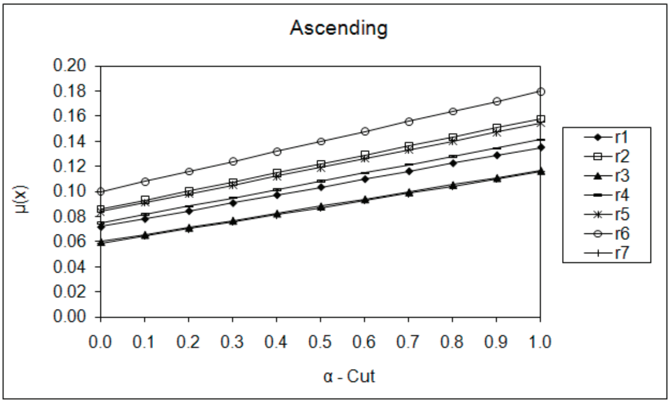

Fig. 5. Technicians' ascending fuzzy values at different α-Cut.

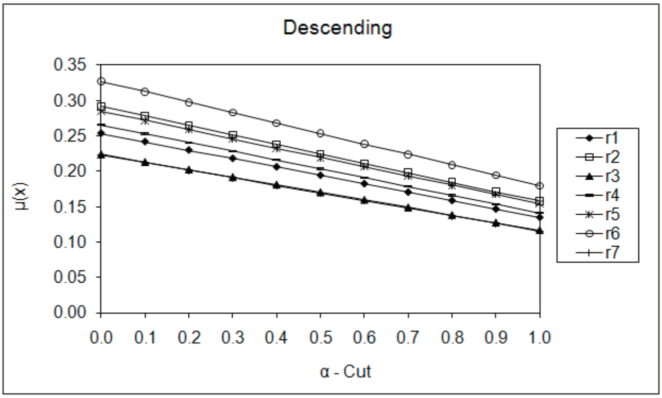

Fig. 6. Technician s' descending fuzzy values at different α-Cut.

Tables 7and 8 show the fuzzy mean and fuzzy spread values for each technician calculated using two techniques;

1. Table 7 using Eq. (17) and Eq. (18) after Chen and Cheng[22],
2. Table 8 using Eq. (19) and Eq. (20) after Lee and Li[23] .

$$\text{Fuzzy spread } (\sigma) = (c-a)/2 \tag{17}$$

$$\text{Fuzzy mean } (\mu) = (a+2b+c)/4 \tag{18}$$

$$\text{Fuzzy spread } (\sigma) = (3a^2+4b^2+3c^2-2ab-4ac-4bc)/80 \tag{19}$$

$$\text{Fuzzy mean } (\mu) = (a+2b+c)/4 \tag{20}$$

The greater the mean is the more preferred the alternative. Therefore, the resulting rated technicians were P6, P2, P5, P4, P1, P3, and P7 as was shown by the previous methods.

Table 7. The fuzzy mean and fuzzy spread values for different alternatives by Eq. (17) and Eq. (18) after Chen and Cheng[22].

Fuzzy Mean / spread	technician **1**	technician **2**	technician **3**	technician **4**	technician **5**	technician **6**	technician **7**
Fuzzy spread **(σ)**	0.09	0.10	0.08	0.10	0.10	0.11	0.08
Fuzzy mean **(μ)**	0.15	0.17	0.13	0.16	0.17	0.20	0.13

Table 8. The fuzzy mean and fuzzy spread values for different alternatives by Eq. (19) and Eq. (20) after Lee and Li[23].

Fuzzy Mean / spread	technician **1**	technician **2**	technician **3**	technician **4**	technician **5**	technician **6**	technician **7**
Fuzzy spread **(σ)**	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Fuzzy mean **(μ)**	0.15	0.17	0.13	0.16	0.17	0.20	0.13

6. Conclusions

Decisions are made today in increasingly complex environments. In many cases, the use of experts in various fields is necessary, different value systems are to be taken into account, *etc*. In many of such decision-making settings the theory of fuzzy decision-making can be of use. Fuzzy group decision-making can overcome this complexity, uncertainty, lack of complete information, *etc*.

Two techniques were used in this work for ranking alternatives; the preference relation using the α-cut and the fuzzy mean and spread using probability distribution. The results of the proposed framework indicate the following:

1. The proposed technique can handle multigoals' problems effectively. The presented framework proved its capability to select the most appropriate technician within a group of suggested proposed alternatives even within unequal important attributed variables.

2. The model can also provide ranking group of technicians working in a factory. Its adaptibility provides the ability to modify its decision making in response to changes in the behaviour of the system in real-time, thus maintaining its performance superiority over other used models.

3. Finally, the proposed algorithm has the capability to deal with similar types of the same situations such as: ranking the best factories to deal with, the best technician in the factory, etc. In general, the proposed method provides accurate selection and can be used easily in industry.

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نظام مساندة قرار اختيار العامل المناسب باستخدام نموذج هلامي متعدد المعايير

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المستخلص. يعتبر اختيار أفضل عامل من العمليات المؤثرة بشكل عام على اقتصاديات التصنيع. هذا البحث يقدم نموذجًا هلاميًا متعدد المعايير لاتخاذ قرار اختيار انسب عامل بين العمال المتنافسين في أي مؤسسة صناعية. العامل المختار لا بد أن يفي المتطلبات من ناحية المهارات التصنيعية والمهارات البشرية. هذه المتطلبات تحتوي على عناصر ذات غموض وعدم دقة خاصة من ناحية العناصر البشرية. بسبب عدم تيقن ونقص المعلومات الدقيقة عن مهارات العامل التصنيعية والبشرية، يجب الوصول إلى تقنية للاختيار تعتمد على دقة البيانات المتاحة. تعتمد تقنية الاختيار في هذا البحث على المنطق الغائم باستخدام العناصر الغائمة باستخدام طريقة القيم المتوسطة الغائمة وذلك للوصول لأنسب العمال بالنسبة لبعضهم البعض. تم تطبيق خطوات هذه التقنية في مثال توضيحي لاتخاذ قرار اختيار أنسب عامل تبعا للمنهج المقدم. في العموم هذه الطريقة قدمت اختيار دقيق لأفضل عامل وأيضا هي طريقة سهلة التطبيق في الصناعة.