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Fuzzy AHp and Topsis Techniques for Employee Recruitment

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ABSTRACT

Background: Today, human resources are one of the important assets of any companies. The main goal of organizations is to seek more powerful ways to determine the priority of personnel who applied for a job. This study is intended to improve employee recruitment process by development of a fuzzy rule based Decision support system. This fuzzy decision support system (FDSS) is applied to evaluate the best employees by qualitative criteria. Most recruitment criteria are qualitative linguistic variables, thus we applied fuzzy logic to convert linguistic variable to a fuzzy number. We design a fuzzy rule based decision support system by Matlab (Matrix Laboratory) software. The obtained result by FDSS is compared with a result of fuzzy Toppsis method (fuzzy MCDM Method) to confirm the reliability and validity of FDSS.

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INTRODUCTION

Nowadays, the importance of human resource factor and its unique role as the strategic recourse in the organization become more tangible than the past time. The attention given to the topic of employee recruitment by researchers has increased considerably in recent years [1, 2]. Employee or personnel performances such as capability, knowledge, skill, and other abilities play an important role in the success of an organization. Great deal of attention in literature was given for the selection of eligible and adequate person among alternative rivals and extensively conducted review can be found in [3] given the numerous topics that have been addressed by researchers and the large number of studies that have been published. The objective of all paper is a selection process which depends mainly on assessing the differences among candidates and predicting the future performance.

The selection of qualified individuals for certain posts is one of the most difficult tasks either in larger or smaller companies and requires an organized system. Indeed, one of the major concerns of Human resource managers is the subject of employee recruitment. Unfair choice in employee recruitment will impose plentiful loss in the future. The loss will contain various dimensions such as financial, cultural and etc.

In the past, organizations had considerably stressed on the employment test. These tests generally involved to assess the Medical condition, Functional characteristics, Behavioral and morphological character, Psychological character and scientific character of applicants. In fact, the result of these tests shows the deserving applicant who is able to be recruited. The weakness of this selection process is the crisp approach to the selection. Furthermore, as it will be mentioned, most of the recruitment criteria in employment tests are qualitative variables, so quantitative assessments will increase the inaccuracies in validity and reliability.

Under many conditions, crisp data are inadequate to model real-life situations. Since human judgment including preferences are often vague and cannot estimate his preference with an exact numerical value. A more realistic approach may be to use linguistic assessments instead of numerical values. In other words, the ratings and weights of the criteria in the problem are assessed by means of linguistic variables.[1, 5,6]. With this respect, fuzzy logic gets a peculiar position at human resource. As it is mentioned most dimensions of human resource are qualitative variables. Any object in fuzzy logic is shown by a Figure between 0 and 1.

In this paper we are planning to develop a generic decision support system which removes the weakness of employment test. From a practical viewpoint, for handling HRM problems, once a decision support system (DSS) established, can do the work. The DSS is a computer-based information system that combines models

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and data in an attempt to solve unstructured problems with extensive user involvement through a friendly user's interface [7]. Actually, for better design of DSS, we develop a fuzzy Topsis. Then we use fuzzy Topsis to develop a fuzzy decision support system (FDSS). By comparison of conclusion of two mentioned methods, we approved the reliability and validity of FDSS. The steps of this research are shown at Fig 1.

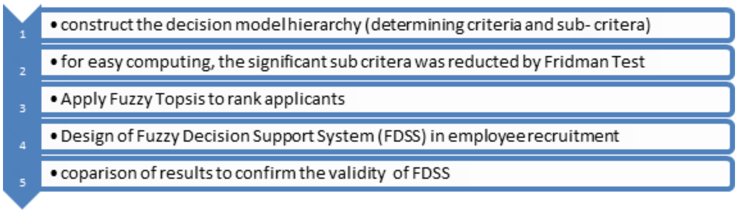

Fig. 1: Steps of research method.

The implementation of this research was at one of biggest company at auto industry in Middle East which we hereinafter call IKCO. The deputy of human resource in IKCO is the pilot of this research. Indeed, the paper is written to solve the problem of employment at this mega company. IKCO (formerly called Iran National before the Islamic revolution) was established 1963 and is Iran's largest motor vehicle producer and industrial conglomerate. The Total staff of this company is more than thirty five thousand. In this respect, it is crucial to design a FDSS to automate the process of employee recruitment. In order to facilitate the process of development of FDSS, we design the employee recruitment model for three applicants who are well qualified by the employment tests for job vacancy at IKCO human resource deputy. The assessment of these applicants was done by four senior managers at human resource deputy of IKCO.

The FDSS was developed by Matlab (Matrix Laboratory).by conforming FDSS, many problems of employee recruitment will be solved. It is mention that this software cannot be used instead of employment test, actually this FDSS is a supplementary system which removes the weakness of the traditional employee recruitment which is merely based on employment tests. The current FDSS is used for qualified applicants who are passed the employment tests.

2- Model design of employee recruitment:

In most reviews of recruitment research, authors [8] have offered organizing models of the recruitment process. Considering to the importance of employee tests as the one of the major common method in employee recruitment, in the current paper, researcher is tried the best to design the framework of research based on criteria of employee tests. Fig 2 is shown some of major tests which are common in employee recruitment. The criteria and sub criteria are adopted from those tests.

Psychological Tests	**Knowledge Tests**	**Performance Tests**	**Behavior and Attitude Test**	**Medical Test**
✓ Minnesota Multiphasic Personality Inventory & global 5 ✓ California Psychological Inventory ✓ Guilford ZimmermanTemperament Survey ✓ Watson – Glaser Critical Thinking Appraisal ✓ Owens Creativity Test ✓ Myers – Briggs – Type Indicator	✓ Leadership opinion questionnaire ✓ General aptitude test battery	✓ Stromberg Dexterity test ✓ Revised Minnesota Paper from Board Test ✓ Minnesota Clerical Test ✓ Job Simulation Test	✓ Honesty Test ✓ Work opinion questionnaire	✓ Drug Tests ✓ Genetic screening ✓ Medical screening

Fig. 2: Some of major tests for employee recruitment

By studies of tests, we have found five major criteria and thirty two sub criteria. These criteria and sub criteria are most emphasized factors at different company. Based on findings, we develop of employee recruitment model.(Fig 3).

Thirty two sub criteria restricted researcher to design Pair wise comparison questionnaire. Thus we have arranged a Friedman Test to reduce the sub criteria. The questionnaire for that test was conformed and distributed among forty experts of IKCO human resource deputy. This reduction was shown in Fig 4. The reduction which led to twelve sub criteria, enable us to arrange pair wise comparison.

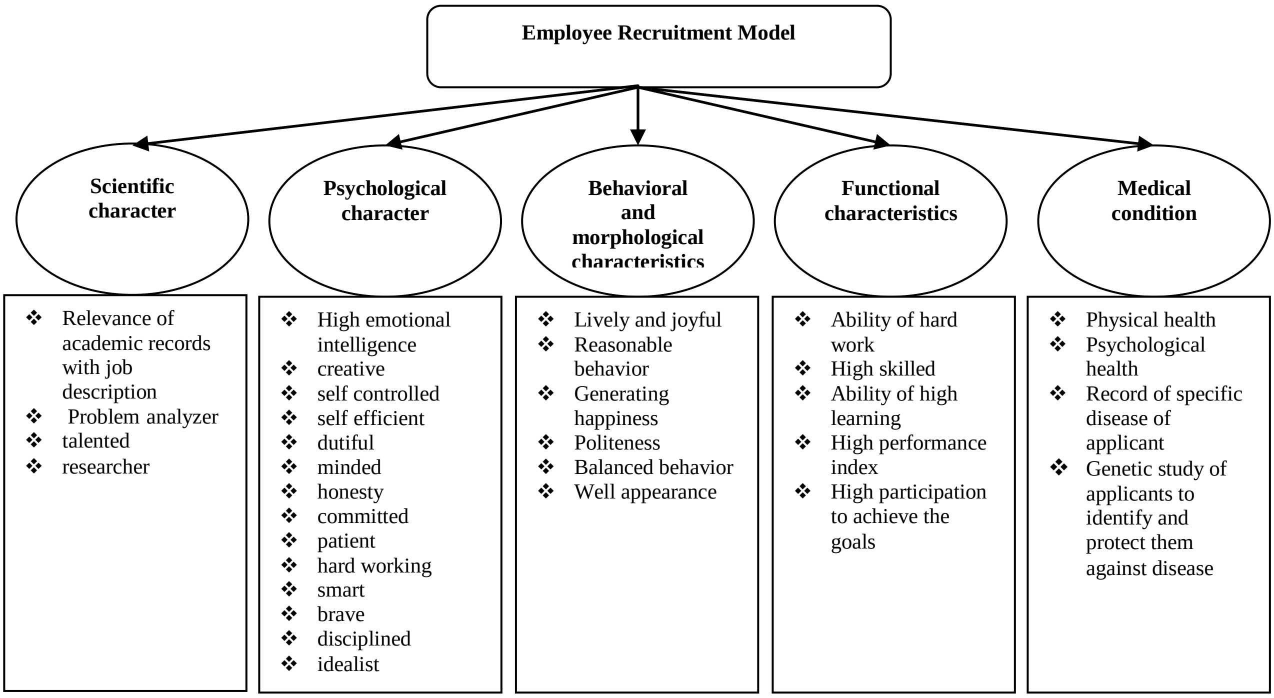

Fig. 3: Employee recruitment model.

Scientific character	Psychological character	Behavioral and morphological characteristics	Functional characteristics	Medical condition
❖ Relevance of academic records with job description ❖ researcher	❖ Creative character ❖ High emotional intelligence ❖ honesty ❖ hard working	❖ Reasonable behavior ❖ Politeness	❖ High performance index ❖ High skilled	❖ Physical health ❖ Psychological health

Fig. 4: Finalized criteria and sub criteria.

3- Fuzzy numbers:

In this part, some primal definitions of fuzzy sets, fuzzy numbers and linguistic variables are explained by [9- 12] the basic definitions and notations below will be used throughout this paper until otherwise stated.

Definition 3.1. 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 $\tilde{A}$ [10].

Definition 3.2. A fuzzy set ~A in the universe of discourse X is convex if and only if

$$\mu_{\tilde{A}}(\lambda x_1 + (1+\lambda)\, x2 \geq \min(\mu_{\tilde{A}}(x_1), \mu_{\tilde{A}}(x_2)) \quad (1)$$

For all x1; x2 in X and all $\lambda \in [0, 1]$ where min denotes the minimum operator [13]

Definition 3.3. The height of a fuzzy set is the largest membership grade attained by any element in that set. A fuzzy set $\tilde{A}$ in the universe of discourse X is called normalized when the height of $\tilde{A}$ is equal to 1 [13].

Definition 3.4. A fuzzy number is a fuzzy subset in the universe of discourse X that is both convex and normal. Fig. 1 shows a fuzzy number $\tilde{N}$ in the universe of discourse X that conforms to this definition [10].

Definition 3.5. The α-cut of fuzzy number $\tilde{N}$ is defined as

$$\tilde{N}^{\alpha} = \{x_i : {}^{\mu}{}_{\tilde{N}}(x_i) \geq \alpha,\ x_i \in x\} \qquad \text{Where } \alpha \in [0\ 1] \quad (2)$$

The symbol $\tilde{N}^{\alpha}$ represents a non-empty bounded interval contained in X, which can be denoted by $\tilde{N}^{\alpha} = [\tilde{N}_l^{\alpha}, \tilde{N}_u^{\alpha}]$, $\tilde{N}_l^{\alpha}$ and $\tilde{N}_u^{\alpha}$ are the lower and upper bounds of the closed interval, respectively [10,14]. For a fuzzy number $\tilde{N}$, if $\tilde{N}_l^{\alpha} > 0$ and $\tilde{N}_u^{\alpha} \leq 1$ for all $\alpha \in [0,1]$, then $\tilde{N}$ is called a standardized (normalized) positive fuzzy number [11].

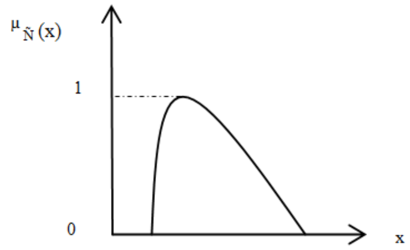

Fig. 5: Fuzzy number Ñ.

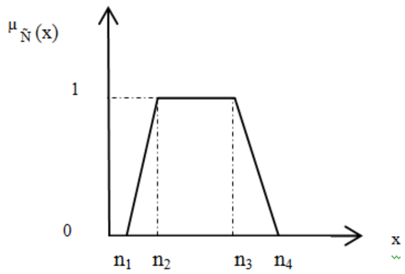

Fig. 6: Trapezoidal Fuzzy number Ñ.

<u>Definition 3.6</u>. A positive trapezoidal fuzzy number (PTFN) Ñ can be defined as (n_1; n_2; n_3; n_4), shown in Fig. 6. The membership function, μ Ñ (x) is defined as [10].

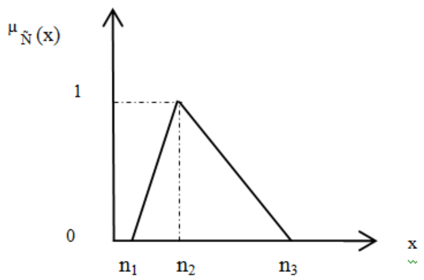

Fig. 7: Triangular Fuzzy number Ñ.

$$\mu_{\tilde{N}}(x) = \begin{cases} 0 & x < n1 \\ \frac{x-n1}{n2-n1} & n1 \le x \le n2 \\ 1 & n2 \le x \le n3 \\ \frac{x-n4}{n3-n4} & n3 \le x \le n4 \\ 0 & x > n4 \end{cases} \tag{3}$$

<u>Definition 3.7</u> A positive Triangular fuzzy number Ñ can be defined by a triplet (n1, n2, n3) as shown in Fig 7.in fact, if n2 = n3, then Ñ is called a triangular fuzzy number. The membership function is defined as μ Ñ (x).

$$\mu_{\tilde{N}}(x) = \begin{cases} 0 & x < n1 \\ \frac{x-n1}{n2-n1} & n1 \le x \le n2 \\ \frac{x-n4}{n3-n4} & n2 \le x \le n3 \\ 0 & x > n3 \end{cases} \tag{4}$$

<u>Definition 3.8</u> multiplication, subtraction and addition operations of the triangular fuzzy numbers are expressed below [10]. this operation can easily generalize to trapezoidal fuzzy number [14].

Fuzzy number addition : (a1; b1; c1) ⊕ (a2; b2; c2) = (a1 + a2; b1 + b2; c1 + c2) (5)

Fuzzy number subtraction : (a1; b1; c1) ⊖ (a2; b2; c2) = (a1 - a2; b1 - b2; c1 - c2)

Fuzzy number multiplication : (a1; b1; c1) ⊗ (a2; b2; c2) = (a1 × a2; b1 × b2; c1 × c2)

<u>Definition 3.9:</u> A non-fuzzy number r can be expressed as (r, r, r, r). By the extension principles [15]

<u>Definition 3.10</u> While variables in mathematics usually take numerical values, in fuzzy logic applications, the non-numeric linguistic variables are often used to facilitate the expression of rules and facts. A linguistic

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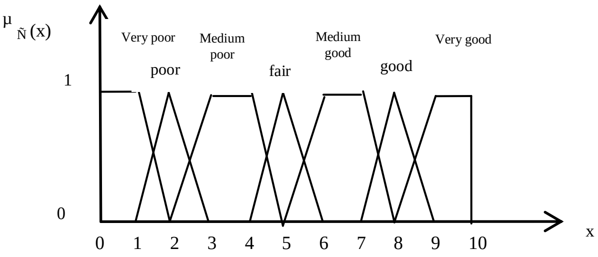
variable is a variable whose values are expressed in linguistic terms. The concept of a linguistic variable is very useful in dealing with situations which are too complex or not well defined to be reasonably described in conventional quantitative expressions.(Fig 8).



Linguistic variables	Fuzzy Number
Very poor	(0,1,1,2)
Poor	(1,2,2,3)
Medium poor	(2,3,4,5)
Fair	(4,5,5,6)
Medium good	(5,6,7,8)
Good	(7,8,8,9)
Very good	(8,9,9,10)

Fig. 8: Linguistic variables for rating.

4- Fuzzy Topsis:

In fact, employee recruitment model is a group multiple-criteria decision-making (GMCDM) problem, which may be described by means of the following sets:

I. a set of K decision-makers called E ={D1;D2; . . . ;DK};
II. a set of m applicants called F={A;B; . . . }
III. a set of n criteria, C ={C1;C2; . . . ;Cn}
IV. a set of s Sub criteria, s={C1;C12; . . . ;C21;C22;….;C31;C32….}

To aggregate the fuzzy number, a good aggregation method should be considered the range of fuzzy rating of each decision-maker thus Assumed that a decision group has K decision makers, and the fuzzy rating of each decision maker can be represented as a positive trapezoidal fuzzy number. Let the fuzzy ratings of all decision makers be trapezoidal fuzzy numbers Ũk =(ak; bk;ck; dk), k = 1; 2; . . . ;K. Then the aggregated fuzzy rating can be defined as:

Ũ=(a; b; c; d); k = 1; 2; . . . ;K. where: a= min {ak}; b=1/K $\sum_{k=1}^{k} bK$; c= 1/k 1/K $\sum_{k=1}^{k} cK$; d =max{dk}. (6)

We have to follow up the following steps to get the result:

A. Considering the different importance of each criterion and the weight of each criterion which are calculated by pair-wise comparison by using Geometric mean , the weighted matrix is constructed as

$$\tilde{N} = [\tilde{I} \times \tilde{N}_{ij}] \quad , \tilde{I} = (i,i,i,i) \qquad (7)$$

$$Geometric\ mean = \sqrt[m]{n_1 \times n_2 \times n_3 \times \dots \times n_m} \qquad (8)$$

B. To avoid complexity, in this research we have defined criteria in beneficial mode so the normalized fuzzy-decision matrix can be represented as

$$\tilde{U} = [\tilde{N}_{ij}]_{m \times n} , \quad \tilde{N} = \left(\frac{a_{ij}}{d_j^*}, \frac{b_{ij}}{d_j^*}, \frac{c_{ij}}{d_j^*}, \frac{d_{ij}}{d_j^*}\right) , \quad d_j^* = \max d_{ij} , \qquad (9)$$

C. According to the normalized fuzzy decision matrix, normalized positive trapezoidal fuzzy numbers can also approximate the elements $\tilde{N}_{ij}$ ∀i; j. Then, the fuzzy positive-ideal solution (FPIS, A^+) and fuzzy negative-ideal solution(FNIS, A^-) can be defined as

$$A^+ = (\tilde{N}_1^+, \tilde{N}_2^+, \dots \tilde{N}_n^+), \qquad A^- = (N_1^-, N_2^-, \dots N_n^-)$$

$$\tilde{N}_j^+ = max\, \tilde{N}_{ij} \text{ , j=4 ,} \qquad \tilde{N}_j^- = min\, \tilde{N}_{ij} \text{ , j=1} \qquad (10)$$

D. The distance of each criterion from A^+ and A^- can be currently calculated as

$$d^+ = \sum_{i=1}^{n} d_v (A^+, \tilde{N}_{ij}) \qquad d^- = \sum_{i=1}^{n} d_v (A^-, \tilde{N}_{ij})$$

$$d_v(\tilde{N}, \tilde{U}) = \sqrt{1/4[(n_1 - u_1)^2 + (n_2 - u_2)^2 + (n_3 - u_3)^2 + (n_4 - u_4)^2} \qquad (11)$$

A closeness coefficient is defined to determine the ranking order of all possible applicants. The closeness coefficient (CCi) of each applicant is calculated as:

$$CC_i = \frac{d_i^-}{d_i^- + d_i^+} \qquad (12)$$

In order to describe the assessment status, we divide the closeness coefficient into the interval [0, 1] and five sub-intervals. Five linguistic variables with respect to the sub-intervals are defined to divide the assessment status of applicants. (Fig 9.1)

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Closeness coefficient (CCi)	Assessment status:
CCi ∈ [0,0.2)	Do not recommend
CCi ∈ [0.2,0.4)	Recommend with high risk
CCi ∈ [0.4,0.6)	Recommend with low risk
CCi ∈ [0.6,0.8)	Approved
CCi ∈ [0.8,1)	Approved and preferred

Fig. 9.1: Approval status.

5- Proposed model for employee recruitment:

In the following, first, the outline of fuzzy Topsis is shown in Fig 9 As the hierarchical structure of decision problem (Fig 9) and then the fuzzy Topsis method is applied to rank the applicants at the employee recruitment problem.

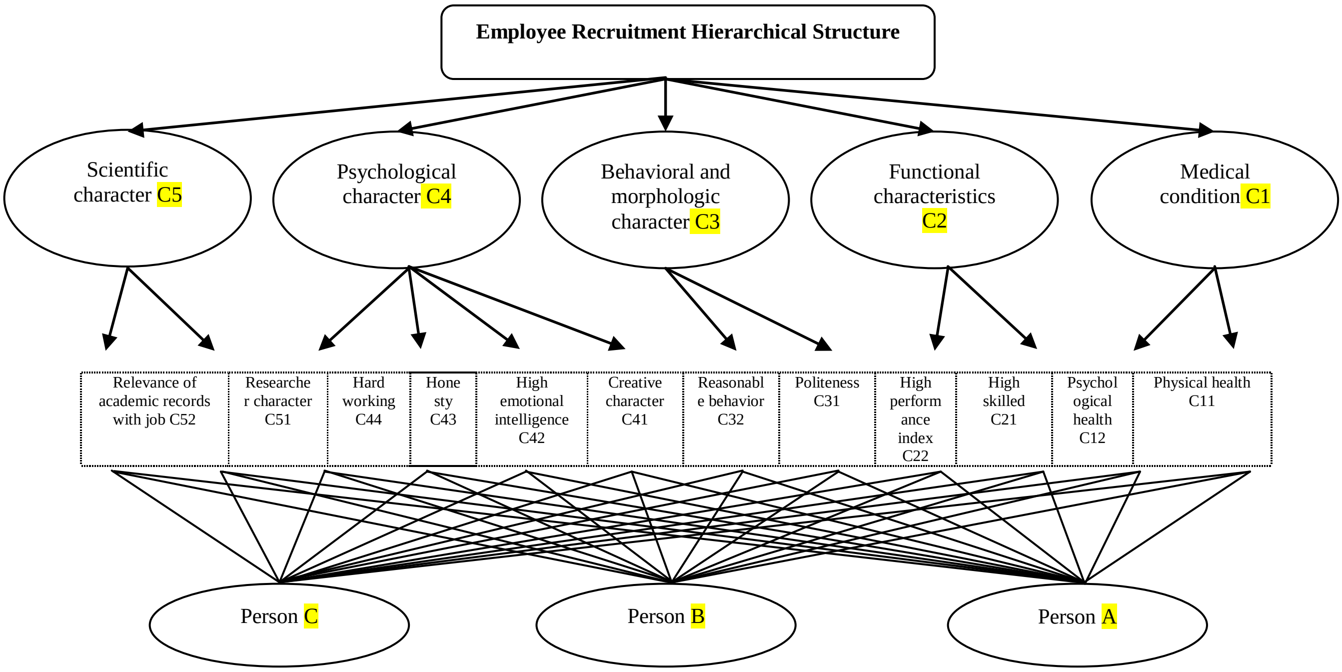

Fig. 9.2: Employee recruitment hierarchical structure.

Step 1: The first step of fuzzy Topsis consists of developing a hierarchical structure of the assessment problem. After developing the hierarchy, decision makers have to determine the relative weights of each criterion and sub criterion. Weights are determined by using pair-wise comparison between each pair of criteria. To determine relative weights, four decision makers are asked to make pair-wise comparison using a (1-5) preference scale (Fig 1). The consistency rate of all pair wise comparison matrix has been checked and approved. Fig 10 is shown one of the pair wise comparisons between main criteria of employee recruitment hierarchical structure.

All pair wise comparison has done by four decision maker. Fig 10 is the average matrix of all view points of decision makers. The result of other pair wise comparison among sub criteria was shown in Fig 11.

Pair wise comparison mean of four manager's view points	C1	C2	C3	C4	C5	Geometric mean	Normalized weight
C1	1.00	3.94	4.16	0.64	2.63	1.94	0.31
C2	0.25	1.00	1.19	0.22	1.19	0.60	0.10
C3	0.24	0.84	1.00	0.27	0.50	0.49	0.08
C4	1.57	4.47	3.66	1.00	3.56	2.47	0.40
C5	0.38	0.84	2.00	0.28	1.00	0.71	0.11
Sum						6.21	1.00

Fig. 10: Normalize weight of each criterion by geometric mean.

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Criteria	Sub-Criteria	Weight of Criteria	Weight of Sub-criteria	Total weight of each criterion (multiplication criteria & sub criteria)
C1	C11	0.31	0.35	0.11
	C12		0.65	0.2
C2	C21	0.1	0.63	0.06
	C22		0.37	0.04
C3	C31	0.08	0.53	0.04
	C32		0.47	0.04
C4	C41	0.4	0.32	0.13
	C42		0.22	0.09
	C43		0.26	0.10
	C44		0.2	0.08
C5	C51	0.11	0.46	0.05
	C52		0.54	0.06

Fig. 11: Total Normalized weight of each sub criterion by geometric mean.

Step2: The assessment of three applicants was done by four decision makers. This assessment was based on linguistic variable. Fig 12 is shown the fuzzy number which is correspondent to each linguistic variables. For example the applicant A, was assessed by D1 at C11, (very good) so

The correspondent trapezoidal fuzzy number base on Fig 8 is (8, 9, 9, and 10). The average of trapezoidal fuzzy number was done by using Eqs. (6).

Step3: weighted decision table was constructed by the result of Fig 11 and Fig 12. By using Eqs. (7), we converted the Normalized weight of each sub criterion to the trapezoidal fuzzy number. (Eqs. 7). Fig 13 is shown fuzzy weight of applicants comparably to sub criteria.

Step 4: conforming the decision matrix of fuzzy Topsis which is shown in (Fig 14).

Step 5: calculating Normalized decision matrix of fuzzy Topsis by using Eqs 9 which is shown in (Fig 15).

Step 6: Determining FPIS and FNIS by using Eqs. 10 which is shown in (Fig 16).

Step 7: calculating Distances between A, B, C and A^- and A^+ with respect to each criterion by using Eqs. 11 which are shown in (Fig 17& Fig 18)

Step 8: calculating CCi by using Eqs.12 which is shown in Fig 19.

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Criteria	Sub criteria	applicants	Decision maker				Average of trapezoidal fuzzy number
			D1	D2	D3	D4	
C1	C11	A	(8,9,9,10)	(7,8,8,9)	(7,8,8,9)	(7,8,8,9)	(7,8.3,8.7,10)
		B	(5,6,7,8)	(7,8,8,9)	(8,9,9,10)	(7,8,8,9)	(5,7.8,8.2,10)
		C	(8,9,9,10)	(8,9,9,10)	(8,9,9,10)	(8,9,9,10)	(8,9,9,10)
	C12	A	(7,8,8,9)	(8,9,9,10)	(7,8,8,9)	(7,8,8,9)	(7,8.3,8.7,10)
		B	(7,8,8,9)	(7,8,8,9)	(4,5,5,6)	(5,6,7,8)	(4,6.7,7,9)
		C	(7,8,8,9)	(8,9,9,10)	(8,9,9,10)	(7,8,8,9)	(7,8.5,9,10)
C2	C21	A	(8,9,9,10)	(7,8,8,9)	(7,8,8,9)	(8,9,9,10)	(7,8.5,9,10)
		B	(7,8,8,9)	(7,8,8,9)	(8,9,9,10)	(7,8,8,9)	(7,8.3,8.7,10)
		C	(8,9,9,10)	(5,6,7,8)	(7,8,8,9)	(8,9,9,10)	(5,8,8.3,10)
	C22	A	(5,6,7,8)	(7,8,8,9)	(8,9,9,10)	(5,6,7,8)	(5,7.3,7.8,10)
		B	(7,8,8,9)	(8,9,9,10)	(8,9,9,10)	(4,5,5,6)	(4,7.8,8.2,10)
		C	(7,8,8,9)	(8,9,9,10)	(7,8,8,9)	(7,8,8,9)	(7,8.3,8.7,10)
C3	C31	A	(5,6,7,8)	(7,8,8,9)	(8,9,9,10)	(7,8,8,9)	(5,7.8,8.2,10)
		B	(8,9,9,10)	(8,9,9,10)	(8,9,9,10)	(8,9,9,10)	(8,9,9,10)
		C	(7,8,8,9)	(8,9,9,10)	(7,8,8,9)	(7,8,8,9)	(7,8.3,8.7,10)
	C32	A	(7,8,8,9)	(7,8,8,9)	(4,5,5,6)	(5,6,7,8)	(4,6.7,7,9)
		B	(7,8,8,9)	(8,9,9,10)	(8,9,9,10)	(7,8,8,9)	(7,8.5,9,10)
		C	(8,9,9,10)	(7,8,8,9)	(7,8,8,9)	(8,9,9,10)	(7,8.5,9,10)
C4	C41	A	(7,8,8,9)	(7,8,8,9)	(8,9,9,10)	(7,8,8,9)	(7,8.3,8.7,10)
		B	(8,9,9,10)	(5,6,7,8)	(7,8,8,9)	(8,9,9,10)	(5,8,8.3,10)
		C	(5,6,7,8)	(7,8,8,9)	(8,9,9,10)	(5,6,7,8)	(5,7.3,7.8,10)
	C42	A	(7,8,8,9)	(8,9,9,10)	(8,9,9,10)	(4,5,5,6)	(4,7.8,8.2,10)
		B	(7,8,8,9)	(8,9,9,10)	(7,8,8,9)	(7,8,8,9)	(7,8.3,8.7,10)
		C	(5,6,7,8)	(7,8,8,9)	(8,9,9,10)	(7,8,8,9)	(5,7.8,8.2,10)
	C43	A	(8,9,9,10)	(8,9,9,10)	(8,9,9,10)	(8,9,9,10)	(8,9,9,10)
		B	(7,8,8,9)	(8,9,9,10)	(7,8,8,9)	(7,8,8,9)	(7,8.3,8.7,10)
		C	(7,8,8,9)	(7,8,8,9)	(4,5,5,6)	(5,6,7,8)	(4,6.8,7,9)
	C44	A	(7,8,8,9)	(8,9,9,10)	(8,9,9,10)	(7,8,8,9)	(7,8.5,9,10)
		B	(8,9,9,10)	(7,8,8,9)	(7,8,8,9)	(8,9,9,10)	(7,8.5,9,10)
		C	(7,8,8,9)	(7,8,8,9)	(8,9,9,10)	(7,8,8,9)	(7,8.3,8.7,10)
C5	C51	A	(8,9,9,10)	(5,6,7,8)	(7,8,8,9)	(8,9,9,10)	(5,8,8.3,10)
		B	(5,6,7,8)	(7,8,8,9)	(8,9,9,10)	(5,6,7,8)	(5,7.3,7.8,10)
		C	(7,8,8,9)	(8,9,9,10)	(8,9,9,10)	(4,5,5,6)	(4,7.8,8.2,10)
	C52	A	(7,8,8,9)	(8,9,9,10)	(7,8,8,9)	(7,8,8,9)	(7,8.3,8.7,10)
		B	(7,8,8,9)	(7,8,8,9)	(4,5,5,6)	(5,6,7,8)	(4,6.8,7,9)
		C	(7,8,8,9)	(8,9,9,10)	(8,9,9,10)	(7,8,8,9)	(7,8.5,9,10)

Fig. 12: Average of trapezoidal fuzzy number for each applicant by assessment of decision maker.

Criteria	Sub criteria	applicants	Average fuzzy number (Fig 12)	Normalized Wight (Trapezoidal fuzzy number) of each sub criteria	Multiplication of average fuzzy number and normalized weight
C1	C11	A	(7,8.3,8.7,10)	(0.11, 0.11, 0.11, 0.11)	(0.76,0.9,0.94,1.09)
		B	(5,7.8,8.2,10)	(0.11,0.11, 0.11, 0.11)	(0.54,0.85,0.89,1.09)
		C	(8,9,9,10)	(0.11, 0.11, 0.11, 0.11)	(0.87,0.98,0.98,1.09)
	C12	A	(7,8.3,8.7,10)	(0.2, 0.2, 0.2, 0.2)	(1.41,1.67,1.75,2.02)
		B	(4,6.7,7,9)	(0.2, 0.2, 0.2, 0.2)	(0.81,1.35,1.41,1.81)
		C	(7,8.5,9,10)	(0.2, 0.2, 0.2, 0.2)	(1.41,1.71,1.81,2.02)
C2	C21	A	(7,8.5,9,10)	(0.06, 0.06, 0.06, 0.06)	(0.44,0.54,0.57,0.63)
		B	(7,8.3,8.7,10)	(0.06,0.06, 0.06, 0.06)	(0.44,0.52,0.55,0.63)
		C	(5,8,8.3,10)	(0.06, 0.06, 0.06, 0.06,)	(0.32,0.5,0.52,0.63)
	C22	A	(5,7.3,7.8,10)	(0.04, 0.04, 0.04, 0.04)	(0.19,0.27,0.29,0.37)
		B	(4,7.8,8.2,10)	(0.04, 0.04, 0.04, 0.04)	(0.15,0.29,0.3,0.37)
		C	(7,8.3,8.7,10)	(0.04, 0.04, 0.04, 0.04)	(0.26,0.31,0.32,0.37)
C3	C31	A	(5,7.8,8.2,10)	(0.04, 0.04, 0.04, 0.04)	(0.21,0.33,0.35,0.42)
		B	(8,9,9,10)	(0.04, 0.04, 0.04, 0.04)	(0.34,0.38,0.38,0.42)
		C	(7,8.3,8.7,10)	(0.04, 0.04, 0.04, 0.04)	(0.3,0.35,0.37,0.42)
	C32	A	(4,6.7,7,9)	(0.04, 0.04, 0.04, 0.04)	(0.17,0.28,0.3,0.38)
		B	(7,8.5,9,10)	(0.04, 0.04, 0.04, 0.04)	(0.3,0.36,0.38,0.42)
		C	(7,8.5,9,10)	(0.04, 0.04, 0.04, 0.04)	(0.3,0.36,0.38,0.42)
C4	C41	A	(7,8.3,8.7,10)	(0.13, 0.13, 0.13, 0.13)	(0.9,1.06,1.11,1.28)

		B	(5,8,8.3,10)	(0.13, 0.13, 0.13, 0.13)	(0.64,1.02,1.06,1.28)
		C	(5,7.3,7.8,10)	(0.13, 0.13, 0.13, 0.13)	(0.64,0.93,1,1.28)
	C42	A	(4,7.8,8.2,10)	(0.09, 0.09, 0.09, 0.09)	(0.35,0.69,0.72,0.88)
		B	(7,8.3,8.7,10)	(0.09, 0.09, 0.09, 0.09)	(0.62,0.73,0.77,0.88)
		C	(5,7.8,8.2,10)	(0.09, 0.09, 0.09, 0.09)	(0.44,0.69,0.72,0.88)
	C43	A	(8,9,9,10)	(0.10, 0.10, 0.10, 0.10)	(0.83,0.94,0.94,1.04)
		B	(7,8.3,8.7,10)	(0.10, 0.10, 0.10, 0.10)	(0.73,0.86,0.9,1.04)
		C	(4,6.8,7,9)	(0.10, 0.10, 0.10, 0.10)	(0.42,0.71,0.73,0.94)
	C44	A	(7,8.5,9,10)	(0.08, 0.08, 0.08, 0.08)	(0.56,0.68,0.72,0.8)
		B	(7,8.5,9,10)	(0.08, 0.08, 0.08, 0.08)	(0.56,0.68,0.72,0.8)
		C	(7,8.3,8.7,10)	(0.08, 0.08, 0.08, 0.08)	(0.56,0.66,0.7,0.8)
C5	C51	A	(5,8,8.3,10)	(0.05, 0.05 , 0.05,0.05)	(0.25,0.4,0.42,0.51)
		B	(5,7.3,7.8,10)	(0.05, 0.05, 0.05, 0.05)	(0.25,0.37,0.39,0.51)
		C	(4,7.8,8.2,10)	(0.05, 0.05, 0.05, 0.05)	(0.2,0.39,0.41,0.51)
	C52	A	(7,8.3,8.7,10)	(0.06,0.06,0.06,0.06)	(0.42,0.49,0.52,0.59)
		B	(4,6.8,7,9)	(0.06,0.06,0.06,0.06)	(0.24,0.4,0.42,0.53)
		C	(7,8.5,9,10)	(0.06,0.06,0.06,0.06)	(0.42,0.5,0.53,0.59)

Fig. 13: Fuzzy weight of applicants comparably to sub criteria.

Decision matrix of fuzzy Topsis	C11	C12	C21	C22	C31	C32	C41	C42	C43	C44	C51	C52
A	(0.76,0.9, 0.94,1.09)	(1.41,1.67, 1.75,2.02)	(0.44,0.54, 0.57,0.63)	(0.19,0.27, 0.29,0.37)	(0.21,0.33 ,0.35,0.42)	(0.17,0.28, 0.3,0.38)	(0.9,1.06, 1.11,1.28)	(0.35,0.69, 0.72,0.88)	(0.83,0.94, 0.94,1.04)	(0.56,0.68, 0.72,0.8)	(0.25,0.4, 0.42,0.51)	(0.42,0.49, 0.52,0.59)
B	(0.54,0.85 ,0.89,1.09)	(0.81,1.35 ,1.41,1.81)	(0.44,0.52, 0.55,0.63)	(0.15,0.29 ,0.3,0.37)	(0.34,0.38, 0.38,0.42)	(0.3,0.36,0 .38,0.42)	(0.64,1.02, 1.06,1.28)	(0.62,0.73, 0.77,0.88)	(0.73,0.86, 0.9,1.04)	(0.56,0.68, 0.72,0.8)	(0.25,0.37, 0.39,0.51)	(0.24,0.4, 0.42,0.53)
C	(0.87,0.98, 0.98,1.09)	(1.41,1.71, 1.81,2.02)	(0.32,0.5, 0.52,0.63)	(0.26,0.31, 0.32,0.37)	(0.3,0.35, 0.37,0.42)	(0.3,0.36, 0.38,0.42)	(0.64,0.93, 1,1.28)	(0.44,0.69, 0.72,0.88)	(0.42,0.71, 0.73,0.94)	(0.56,0.66, 0.7,0.8)	(0.2,0.39, 0.41,0.51)	(0.42,0.5, 0.53,0.59)

Fig. 14: Decision matrix of fuzzy Topsis.

FPIS & FNIS	C11	C12	C21	C22	C31	C32	C41	C42	C43	C44	C51	C52
A+	(1,1,1,1)	(1,1,1,1)	(1,1,1,1)	(1,1,1,1)	(1,1,1,1)	(1,1,1,1)	(1,1,1,1)	(1,1,1,1)	(1,1,1,1)	(1,1,1,1)	(1,1,1,1)	(1,1,1,1)
A-	(0.5,0.5, 0.5,0.5)	(0.4,0.4, 0.4,0.4)	(0.51,0.51 ,0.51,0.51)	(0.41,0.41 ,0.41,0.41)	(0.5,0.5, 0.5,0.5)	(0.4,0.4, 0.4,0.4)	(0.5,0.5, 0.5,0.5)	(0.4,0.4, 0.4,0.4)	(0.4,0.4, 0.4,0.4)	(0.7,0.7, 0.7,0.7)	(0.39,0.39 ,0.39,0.39)	(0.41,0.41 ,0.41,0.41)

Fig. 15: Normalized decision matrix of fuzzy Topsis.

d^-	C11	C12	C21	C22	C31	C32	C41	C42	C43	C44	C51	C52
A	0.36	0.46	0.37	0.39	0.33	0.32	0.37	0.41	0.5	0.2	0.42	0.46
B	0.33	0.32	0.36	0.4	0.41	0.48	0.34	0.47	0.46	0.2	0.4	0.32
C	0.41	0.48	0.32	0.45	0.37	0.48	0.31	0.42	0.32	0.19	0.41	0.47

Fig. 16: Determining FPIS and FNIS.

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d^+	C11	C12	C21	C22	C31	C32	C41	C42	C43	C44	C51	C52
A	0.19	0.18	0.17	0.3	0.28	0.38	0.18	0.33	0.12	0.18	0.29	0.18
B	0.29	0.38	0.18	0.33	0.12	0.17	0.28	0.18	0.18	0.18	0.31	0.37
C	0.12	0.18	0.28	0.18	0.18	0.17	0.3	0.29	0.37	0.18	0.34	0.17

Fig. 17: Distances between A, B, C and A^- with respect to each criterion.

Normalized decision matrix of fuzzy Topsis	C11	C12	C21	C22	C31	C32	C41	C42	C43	C44	C51	C52
A	(0.76,0.9, 0.94,1.09)	(1.41,1.67, 1.75,2.02)	(0.44,0.54, 0.57,0.63)	(0.19,0.27, 0.29,0.37)	(0.21,0.33 ,0.35,0.42)	(0.17,0.28, 0.3,0.38)	(0.9,1.06, 1.11,1.28)	(0.35,0.69, 0.72,0.88)	(0.83,0.94, 0.94,1.04)	(0.56,0.68, 0.72,0.8)	(0.25,0.4, 0.42,0.51)	(0.42,0.49, 0.52,0.59)
B	(0.54,0.85 ,0.89,1.09)	(0.81,1.35 ,1.41,1.81)	(0.44,0.52, 0.55,0.63)	(0.15,0.29 ,0.3,0.37)	(0.34,0.38, 0.38,0.42)	(0.3,0.36,0 .38,0.42)	(0.64,1.02, 1.06,1.28)	(0.62,0.73, 0.77,0.88)	(0.73,0.86, 0.9,1.04)	(0.56,0.68, 0.72,0.8)	(0.25,0.37, 0.39,0.51)	(0.24,0.4, 0.42,0.53)
C	(0.87,0.98, 0.98,1.09)	(1.41,1.71, 1.81,2.02)	(0.32,0.5, 0.52,0.63)	(0.26,0.31, 0.32,0.37)	(0.3,0.35, 0.37,0.42)	(0.3,0.36, 0.38,0.42)	(0.64,0.93, 1,1.28)	(0.44,0.69, 0.72,0.88)	(0.42,0.71, 0.73,0.94)	(0.56,0.66, 0.7,0.8)	(0.2,0.39, 0.41,0.51)	(0.42,0.5, 0.53,0.59)

Fig. 18: Distances between A,B,C and A^+ with respect to each criterion.

Computations of Cci	$\sum d^+$	$\sum d^-$	$\sum d^+ + \sum d^-$	**Cci**
A	**2.78**	**4.59**	**7.37**	**0.62**
B	**2.97**	**4.49**	**7.46**	**0.60**
C	**2.76**	**4.63**	**7.39**	**0.63**

Fig. 19: Computations of d^+, d^- and CCi.

Based on Fig 9 all applicants are approved to recruit but applicant C is in the priority of employee recruitment. Applicant A and B are in the subsequent ranking for recruitment.

4- Fuzzy Decision Support System by Matlab:

Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. The mapping then provides a basis from which decisions can be made, or patterns discerned. The process of fuzzy inference involves all of the pieces that are described in the previous sections: Membership Functions, Logical Operations, and If-Then Rules. You can implement two types of fuzzy inference systems in the toolbox of matab: Mamdani-type and Sugeno-type. These two types of inference systems vary somewhat in the way outputs are determined [16, 17].

Fuzzy inference systems have been successfully applied in fields such as automatic control, data classification, decision analysis, expert systems, and computer vision. Because of its multidisciplinary nature, fuzzy inference systems are associated with a number of names, such as fuzzy-rule-based systems and FDSS.

One of the major applications of FDSS is in the qualitative decision. As it was mentioned before employee recruitment is the qualitative problem. Thus the FDSS works a lot in this problem.

Mamdani's fuzzy inference method is the most commonly seen fuzzy methodology. Mamdani's method was among the first control systems built using fuzzy set theory. It was proposed in 1975 by Ebrahim Mamdani [18] as an attempt to control a steam engine and boiler combination by synthesizing a set of linguistic control rules obtained from experienced human operators. Mamdani's effort was based on Lotfi Zadeh's 1973 paper on fuzzy algorithms for complex systems and decision processes [19]

Sugeno, Takagi-Sugeno-Kang, is another method of fuzzy inference which Introduced in 1985 [20] it is similar to the Mamdani method in many respects. The first two parts of the fuzzy inference process, fuzzifying the inputs and applying the fuzzy operator, are exactly the same. The main difference between Mamdani and Sugeno is that the Sugeno output membership functions are either linear or constant.

A typical rule in a Sugeno fuzzy model has the following form

$$z = ax + by + c \qquad (13)$$

Based on mentioned method of fuzzy inference, we have used sugeno method. According to points of decision makers at IKCO Company and further to the problem of coding twelve sub criteria with seven segments of fuzzy membership in Matlab, researcher is used five main criteria with three segments of fuzzy membership. Researchers have used triangular fuzzy number in Matlab.

According to the linguistic variables, researcher defined (6 8 10), (3 5 7), (3 5 7) in order for good, average and poor as the linguistic variables. For designing of fuzzy decision support systems, we have followed the following steps:

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Step1: We have designed the decision matrix as the input of Matlab software. The average fuzzy numbers are converted from linguistic variables which are obtained from four decision maker and three applicants.

Decision matrix as the input of Matlab	C1	C2	C3	C4	C5
A	(3 7.25 10)	(3 7.25 10)	(3 6.5 10)	(3 6.5 10)	(6 8 10)
B	(3 6.5 10)	(3 6.5 10)	(3 7.25 10)	(3 6.5 10)	(3 7.25 10)
C	(6 8 10)	(3 7.25 10)	(6 8 10)	(6 8 10)	(3 7.25 10)

Fig. 20: Decision matrix as the input of Matlab.

Step 2: we have to defuzzy Fig 20 as the inputting of Matlab software. There are lots of defuzzification methods. We have used Mean Value method for defuzzification of triangular fuzzy number. The Eqs 14 is shown the Mean Value method. Fig 21 is shown the defuzzied matrix.

$$defuzzy(A,B,C)=\frac{A+2B+C}{4} \qquad (14)$$

defuzzied matrix	C1	C2	C3	C4	C5
A	6.87	6.87	6.5	6.5	8
B	6.5	6.5	6.87	6.5	6.87
C	8	6.87	8	8	6.87

Fig. 21: Defuzzied matrix.

Step 3: we code the software of fuzzy logic in Matlab. It was based on three linguistic variables with sixteen rules which are determined by experts at IKCO Company. Based on Eqs 13, we have defined the function of Sugeno Model in Eqs. 15. The weights in the function are obtained from Topsis model.

$$Y=0.31C1+0.10C2+0.08C3+0.4C4+0.11C5 \qquad (15)$$

Step 4: we have run the software. Fig 22 is shown the status of applicant A. Fig 23 is shown the status of applicant B. Fig 24 is shown the status of applicant C.

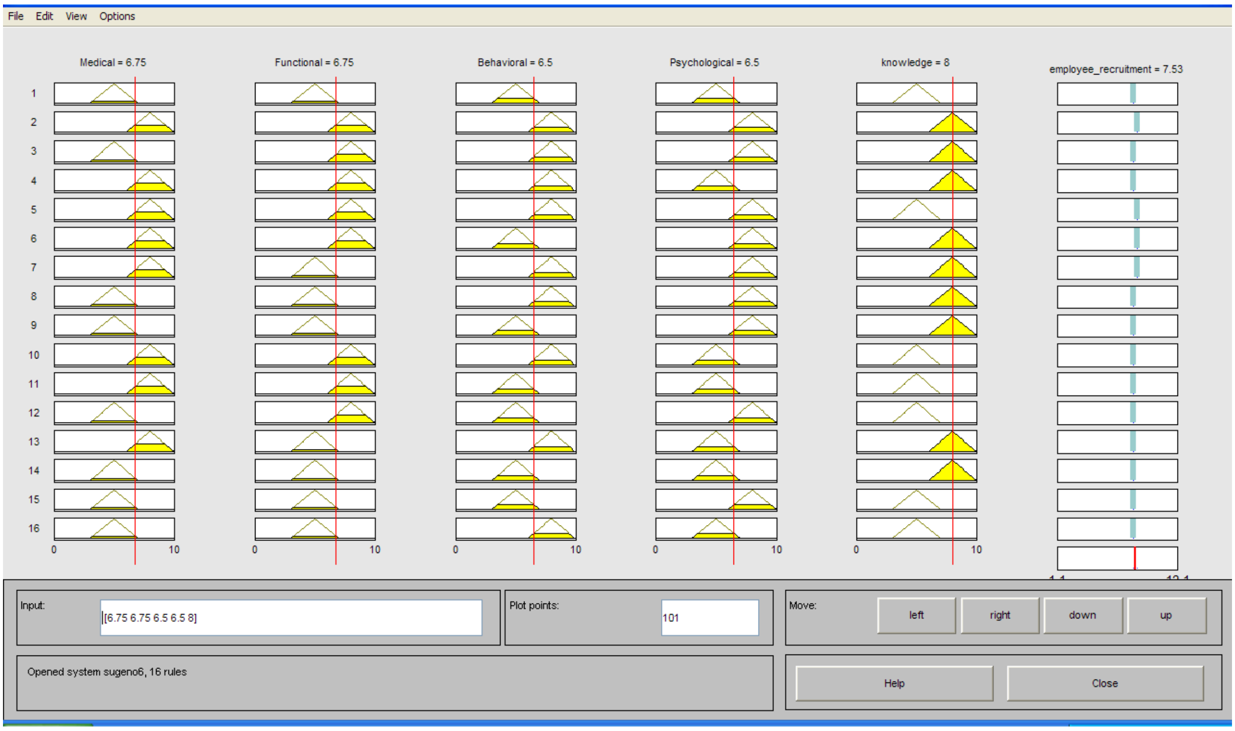

Fig. 22: The status of applicant A.

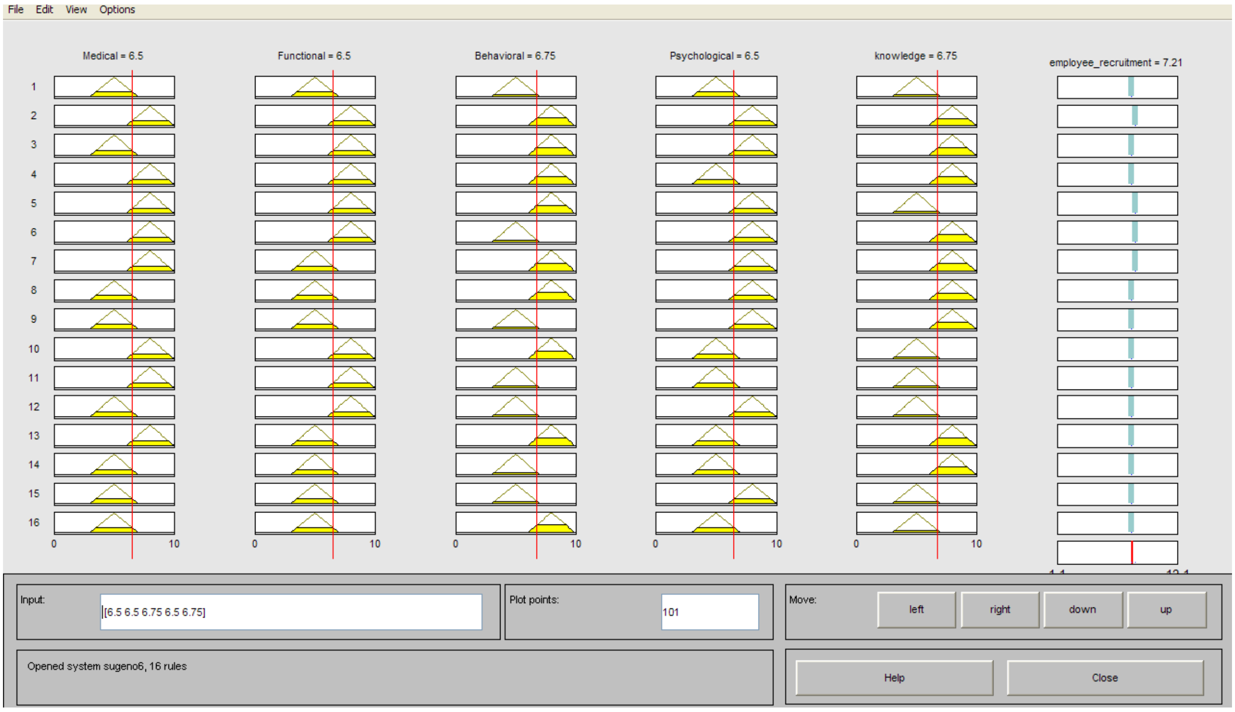

Fig. 23: The status of applicant B.

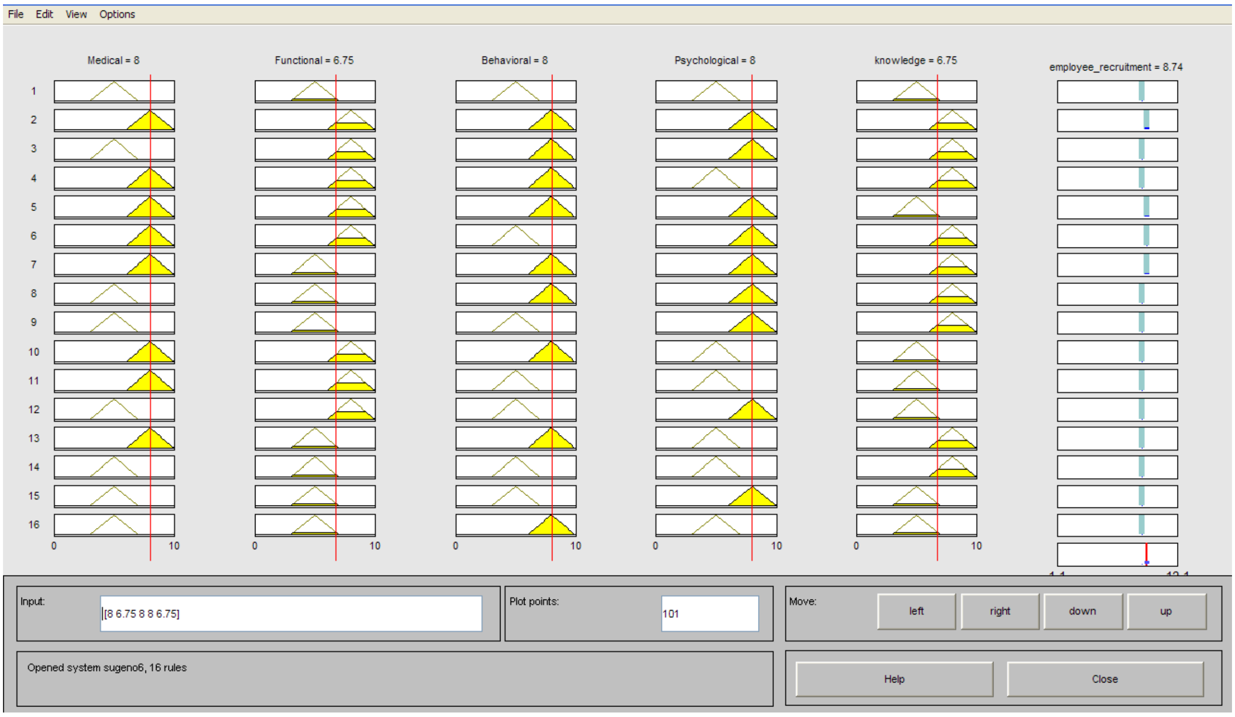

Fig. 24: The status of applicant C.

Based on calculation of software the applicant C with value of 8.74 is in the first priority in recruitment and applicants A and C are in the following ranks with value of 7.53 and 7.21.

5- Conclusion:

In this paper, a fuzzy decision support system has been proposed in employee recruitment. The performance of the proposed method has been compared with fuzzy Topsis method. The result shows the similarity of both methods which will confirm the reliability and validity of FDSS. The proposed FDSS is intelligent which

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omitted the repetitive pair wise comparison among applicants. This FDSS is used in IKCO Company and it can generalize for each department or company. This FDSS can enhance the employee recruitment.

This paper proposes the using FDSS in the employee recruitment as the best tool in qualitative assessments. By inserting the value which is obtained from converting linguistic variables to the fuzzy number, to the Matlab software, the ranking of applicants shows the priority in recruitment.

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