Proceedings of the Workshop on Foundations of Informatics
FOI-2015, August 24-29, 2015, Chisinau, Republic of Moldova

Human Resource Selection Process by Using Various Fuzzy Logic Techniques

Mustafa Tinkir, Burcu Doganalp, Serkan Doganalp

Abstract

Because of the fact that today human resources has been accepted as one of the most important source of competitive advantage of an organization, finding the right person for the job has become as a vital human resource management function. This paper presents mamdani and sugeno type fuzzy inference system modeling techniques being used while group decision making in the fuzzy environment and displays the methods process with an empirical application. For this purpose, as decision makers, two top managers in a business organization that is in the list of First 500 Big Industrial Organizations of Turkey have evaluated decision criteria and the candidates by using linguistic variables for the position of mechanical maintenance manager. These verbal data have been transformed into triangular fuzzy numbers for both modeling techniques. Prediction models have been obtained by using fuzzy logic and ANFIS toolboxes of MATLAB respectively and their applications on process have been realized via Simulink. All obtained prediction results have been compared with table according to prediction performances of techniques. This study shows that for deciding more accurately and effectively in human resource selection process, various fuzzy logic models are considerably suitable as an approach of fuzzy multi-criteria group decision making.

Keywords: Human Resource Selection, Decision Making, Mamdani, Sugeno Fuzzy Inference System.

1 Introduction

Because of that human resources are one of the core competences for an organization to gain and enhance competitive advantage in a knowledge economy [1] today, the enterprises compete with each other for talent. In this context, finding the right person for the vacant job has become one of the most important and indispensable activities [2]. Among the functions of human resource management, human resource selection significantly affects the quality of employees and administration, and hence it has attracted intensive attention and is an important topic for the organizations [1]. Increasing competition in global markets urges organizations to put more emphasis on human resource selection process [3]. The growing importance of human resource selection process, in addition to that it is a very expensive and time taking up activity, makes the approach designing to be used in this process as a prerequisite for the organizations [2], and has brought about the usage of analytical decision making approaches [3]. The human resource selection activity can be described as a decision problem, that it is an uncertain group decision making process, and contains information which is vague and fuzzy [4]. It is clear that decision makers in charge of determining the most appropriate job candidate for the vacant position prefer to use natural language [5]. Because of expressing verbal information, using natural language causes vague information [6]. Decision making can be based on decision makers imprecise perception relying on his/her subjective ideas, experience and beliefs [7]. This situation can be considered also for human resource selection as a decision making process. It is common sense that personnel selectors tend to include as many elements as possible in their decision making process, without being able to clearly define which element has the greatest impact on the outcome of a decision [8]. Decision made under these circumstances is defined as subjective judgment [9]. Many real-world problems including human resource selection have been solved with the fuzzy logic for the last twenty five years [10]. In a vague condition, fuzzy logic approach can provide an attractive connection to represent uncertain information and can aggregate them properly [11]. Since the fuzzy logic approach provides a simultaneous solution to a complex system of competing objectives, it seems to be a proper tool for an organization's staff allocation problem [12]. Fuzzy set theory can be applied to other business problems whenever there is a need to do modeling with imprecise reasoning processes or ambiguity in human decision-making [13]. In this context, fuzzy logic theory appears as an effective tool to incorporate imprecise judgments inherent in the human resource selection process [14]. The purpose of this study is finding the most suitable candidate for the machine maintenance manager position of the selected organization with mamdani and sugeno type fuzzy inference system modeling techniques. Triangular type membership functions are used to constitute mamdani and sugeno type-1 fuzzy inference systems.

2 Research Design and Methodology

2.1 Data Set Development

Human resource selection process for machine maintenance manager position of industrial organization has been realized in respect of Table 2. Accordingly, 5 candidates attended to the interview for the position and they were assessed in terms of decision criteria predetermined by organizations human resource management department. Interview was carried out of 16 points, and candidates' scores were calculated as a percentage. After determining interview scores, two candidates (1. candidate and 4. candidate) scored over 80 points in the interview were subjected to the English test. English test was applied and assessed out of 1200 points. As it can be seen from the Table 2, interview score of the 1. candidate was higher than the score of 4. candidate. It was because of the assessment score in respect to the business knowledge criteria. In contrast, open communication assessment score of the 4. candidate was higher than the 1. candidate. But the English test score of 4. candidate was higher. In this context, the human resource department considered that business knowledge could be improved in the course of time. Therefore 4. candidate was preferred for the proposed position.

Table 1. Human Resource Selection for Machine Maintenance Manager Position of Industrial Organization

Position	Machine Maintenance Manager					
Evaluation Criteria	Criteria Weight	1.Cndt	2.Cndt	3.Cndt	4.Cndt	5.Cndt
Open communication	4	3	2	3	4	3
Drawing lessons from mistakes	3	3	3	2	3	2
Working with strategy and targets	3	3	3	2	3	2
Skill of thinking and learning	3	3	3	2	3	2
Business knowledge	3	3	1	2	1	2
Score	16	93.75%	75%	68.75%	87.5%	68.75%
1.Candidate 4.Candidate	Out of 1200 Out of 1200	584 650	Two candidates scored over 80 points in the interview were subjected to the English test.			
Interpretation	Interview score of the 1. candidate was higher than the score of 4. candidate. It was because of the assessment score in respect to the business knowledge criteria. In contrast, open communication assessment score of the 4. candidate was higher than the 1. candidate. But the English test score of 4. candidate was higher. In this context, the human resource department considered that business knowledge could be improved in the course of time. Therefore 4. candidate was preferred for the proposed position.					

3 Fuzzy Logic Modeling Techniques

3.1 Mamdani Type Fuzzy Logic Model

The field of fuzzy system has been making a big progress motivated by the practical success in modeling and control of industrial process [15]. Fuzzy systems can be used as system modeling. In this case fuzzy modeling provides appropriate system outputs from real experimental data sets. The fuzzy logic model uses a form of quantification of imprecise information (input fuzzy sets) to generate by an inference scheme, which is based on a knowledge base of modeling. The advantage of this quantification is that the fuzzy sets can be represented by a unique linguistic expression, such as small, medium and large, etc. The linguistic representation of a fuzzy set is known as a term, and a collection of such terms defines a term-set, or library of fuzzy sets. Fuzzy logic converts a linguistic modeling strategy usually based on expert knowledge into a systems fuzzy logic modeling strategy. Fuzzy logic is made of four main components: (1) Fuzzifier; (2) Knowledge base containing fuzzy IF-THEN rules and membership functions, (3) Fuzzy reasoning; and (4) Defuzzifier interface. The basic configuration of the fuzzy system with fuzzifier and defuzzifier used in this study is shown in Figure 1.

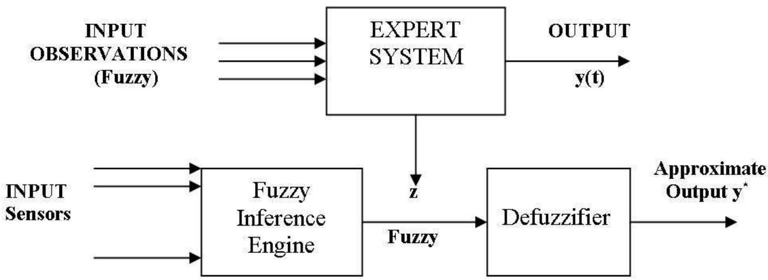

Figure 1. The basic configuration of the fuzzy system

In this paper, a Mamdani type-1 fuzzy logic modeling for human resource selection have been realized and compared with actual selection of selected industrial organization and results of ANFIS type fuzzy logic technique. Primarily we have obtained real data sets from organizations human resource selection process to create inputs and outputs of Mamdani type fuzzy logic model. Fuzzy logic model membership functions and rule bases have been formed by criteria of human resource selection process of the selected industrial organization.

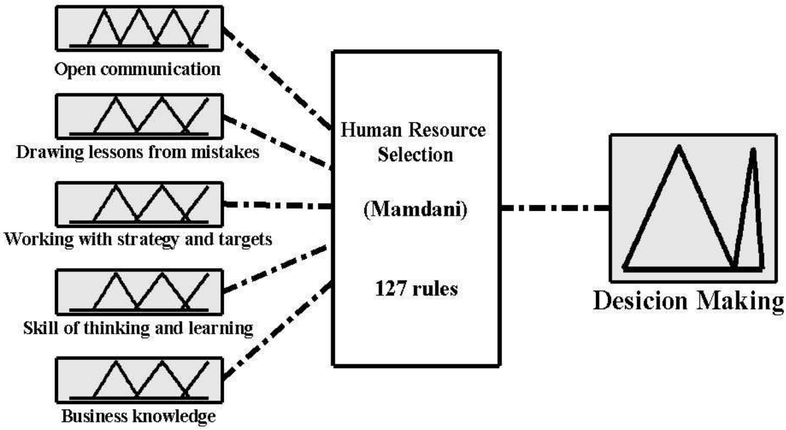

Figure 2. Fuzzy logic modeling for human resource selection

In Figure 2, fuzzy logic modeling for the selected organizations human resource selection process has been shown. In this configuration we can say that fuzzy logic model has five inputs as open communication, drawing lessons from mistakes, working with strategy and targets, skill of thinking and learning, and business knowledge. And also it has single outputs as decision making output. Moreover 127 rules used for mamdani type fuzzy inference model and membership functions for each input and output is given in Figure 3.

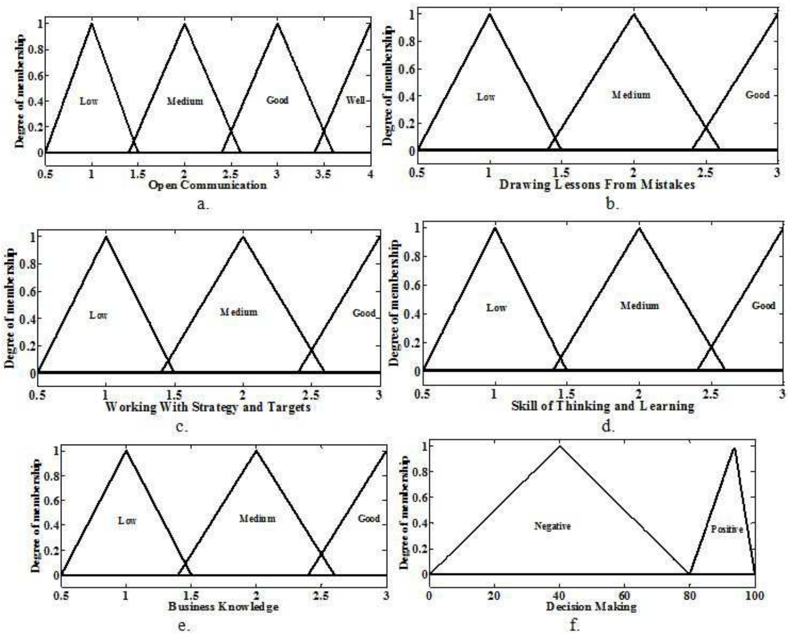

Figure 3. Membership functions of Mamdani type fuzzy logic model: *a. Membership functions of open communication input. b. Membership functions of drawing lessons from mistakes input. c. Membership functions of working with strategy and targets input. d. Membership functions of skill of thinking and learning input. e. Membership functions of business knowledge input. f. Membership functions of decision making output.*

3.2 Sugeno Type Fuzzy Logic Model

Two of the difficulties with the design of any fuzzy logic modeling are the shape of the membership functions and choice of the fuzzy rules. In fact, decision-making logic is the way in which the model output is generated. It uses the input fuzzy sets and the decision is taken according to the values of the inputs. Moreover, the knowledge base comprises knowledge of application domain and the attendant modeling goals. It consists of a database and a fuzzy logic model rule base. The fuzzification uses membership functions to determine the degree of inputs. The purpose of modeling is to obtain suitable outputs according to real human resource selection. In this study, sugeno-type inference system is used to create fuzzy logic model of proposed system. It applies a combination of the least-squares method. Fuzzy logic model of human resource selection has three membership functions for each input. Triangular type membership functions have been used in fuzzification process. Membership functions and rules of sugeno type fuzzy logic model are given in Figure 4. Fuzzy logic rule base is made of 243 rules and these rules have been determined by adaptive neural network based fuzzy inference system (ANFIS) of human resource selection. ANFIS ensures to obtain optimum range of membership functions and rules which are based on real selection data easily. But it permits only one output. Anfis outputs are constant values not fuzzy.

3.3 Adaptive Neural Network

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the network function is determined largely by the connections between elements. We can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements. Commonly neural networks are adjusted, or trained, so that a particular input leads to a specific target output. Such a situation is shown in Figure 5. There, the network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Typically many such input/target pairs are

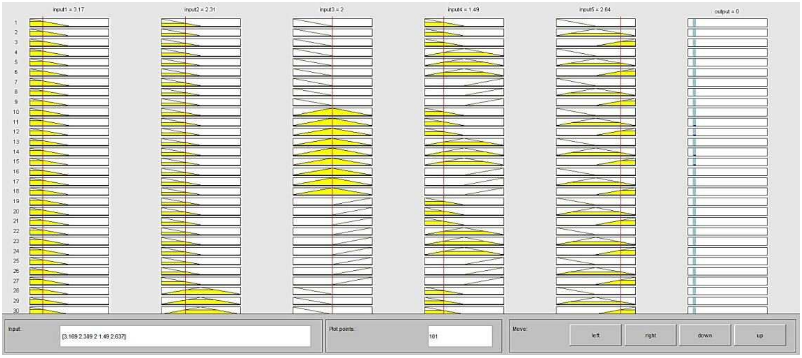

Figure 4. Membership functions and rules of Sugeno type fuzzy logic model

needed to train a network. Neural networks have been trained to perform complex functions in various fields, including pattern recognition, identification, classification, modeling, speech, vision, and control systems.

We have followed these steps for creating ANFIS modeling shown below:

- 20 training and 5 test data have been used for neural network based on ANFIS modeling.
- The number and type of membership functions have been determined.
- Hybrid learning algorithm and 20 epochs have been chosen to train network.

3.4 Hybrid Learning Algorithm

In this study, the forward hybrid learning algorithm has been used for the neural network part of the ANFIS controllers shown in Figure 6.

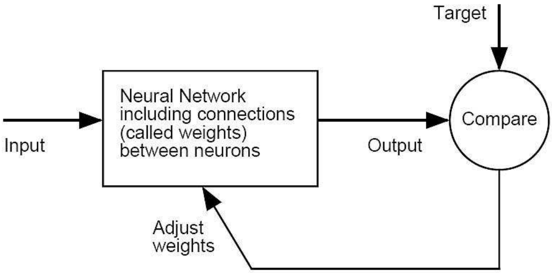

Figure 5. Neural network structure

The hybrid learning algorithm was described in the literature [16,17]. Nearly 20 epochs later, error rate is closed to 2.10-5. In the forward pass of the hybrid learning algorithm, node outputs go forward until layer 4 and the consequent are identified by the least-squares method. When the values of the premise parameters are fixed, the overall output can be expressed as a linear combination of the consequent parameters.

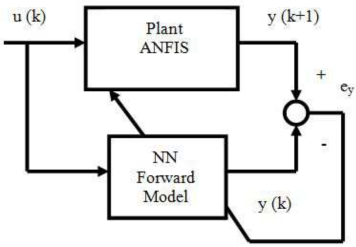

Figure 6. Training of NN forward model

The ANFIS is a fuzzy Sugeno model putting adaptive capability in framework to facilitate learning and adaptation. Such framework makes the ANFIS modeling more systematic and less reliant on expert knowledge. To present the ANFIS architecture, two fuzzy IF-THEN rules based on a first-order Sugeno model are considered:

Rule 1: If (x is A_1) and (y is B_1), then ($f_1 = p_1x + q_1y + r_1$).

Rule 2: If (x is A_2) and (y is B_2), then ($f_2 = p_2x + q_2y + r_2$).

where x and y are the inputs, A_i and B_i are the fuzzy sets, f_i are the outputs within the fuzzy region specified by the fuzzy rule, p_i ; q_i and r_i are the design parameters that are determined during the training process [18]. The ANFIS architecture to implement these two rules is shown in Figure 7, in which a circle indicates a fixed node, whereas a square indicates an adaptive node.

When the premise parameters are not fixed, the search space becomes larger and the convergence of the training becomes slower. A hybrid algorithm combining the least-squares method and the gradient descent method is adopted to solve this problem. The hybrid algorithm is composed of a forward pass and a backward pass. The least-squares method (forward pass) is used to optimize the consequent parameters with the premise parameters fixed. Once the optimal consequent parameters are found, the backward pass starts immediately. The gradient descent method (backward pass) is used to adjust optimally the premise parameters corresponding to the fuzzy sets in the input domain. The output of the ANFIS is calculated by employing the consequent parameters found in the forward pass. The output error is used to adapt the premise parameters by means of a standard backward pass algorithm. It has been proven that the hybrid algorithm is highly efficient in training the ANFIS [19]. Fuzzy logic modeling is by far the most successful applications of the fuzzy set theory and fuzzy inference systems. Due to the adaptive capability of ANFIS, its applications to adaptive modeling and learning modeling are immediate. For this purpose, the adaptive network-based fuzzy inference system has been used to optimize the fuzzy IF-THEN rules and the membership functions to derive a more efficient fuzzy model. The proposed ANFIS model combined the neural network adaptive capabilities and the fuzzy logic qualitative approach [19].

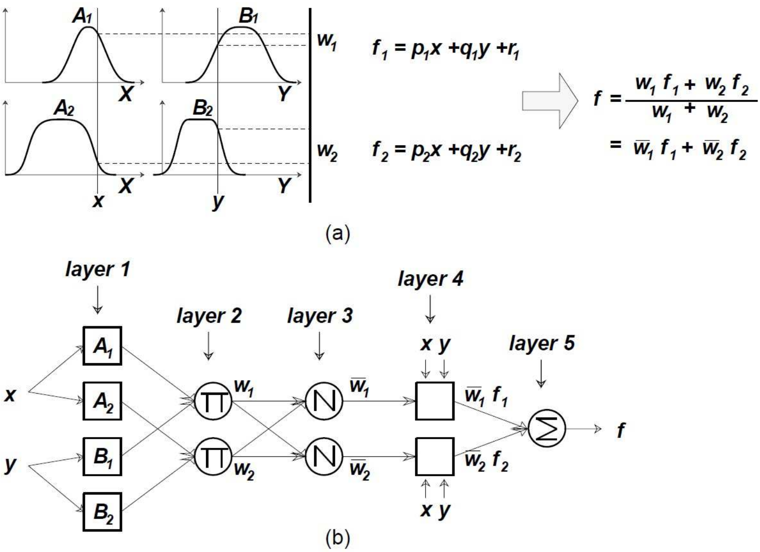

Figure 7. (a) TSK fuzzy inference system with two inputs and two rules. (b) Architecture of ANFIS of first order TSK model with two inputs.

3.5 Defuzzification Process

Once the fuzzy inference system is activated, rule evaluation is performed and all the rules are true and fired. Utilizing the true output membership functions, defuzzification is then applied to determine a crisp control action. The defuzzification is to transform the fuzzy output into an exact model output. For Sugeno-style inference, we have to choose whether wtaver (weighted average) or wtsum (weighted sum) defuzzification method to use. In defuzzification process of sugeno type fuzzy logic modeling of human resource selection, the method of weighted average (wtaver) has been used.

4 Results and Discussion

The effectiveness of the proposed modeling techniques have been tested by using MATLAB/Simulink program and the algorithm given in Figure 8 has been used to form simulation block diagram. The purpose of the models is to find the most appropriate candidate for machine maintenance manager position of the selected industrial organization according to its selection process.

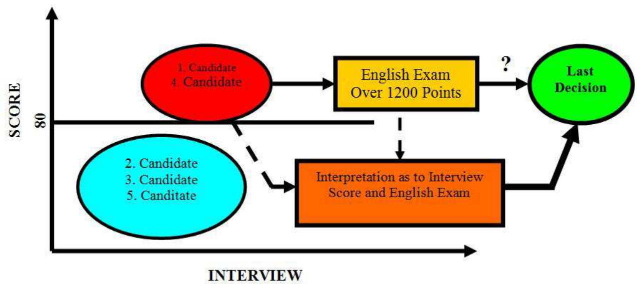

Figure 8. The algorithm used for all Fuzzy Logic Modeling Techniques

Mamdani and ANFIS type models have been created by real interview results of the human resource department and five inputs have been used as decision criteria determined by the department. Last decision linguistic variable was used as single output of the models. Every candidate has been assessed via their curriculum vitae by the human resource department and then the candidates found to be appropriate after the assessment have been invited to the interview. Finally as a last stage in the selection process, two candidates whose interview scores were higher than 80 points were subjected to the English test.

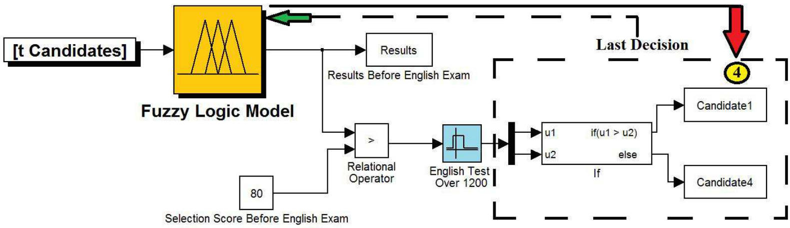

Figure 9. Simulink Diagram for Mamdani and Sugeno Type Fuzzy Logic Modeling

The program for fuzzy models has been written for this purpose by using algorithm and English exam scores of the candidates scored over 80 points in the interview have been added to simulation program to evaluate the selection process. As a result, fuzzy models have been used to select the right candidate instead of human resource departments decision making process. Comparisons of the models with real interview results are given in Table 3. According to the decision of the human resource department for the interview:

1. candidate and 4. candidate scored over 80 points in the interview were subjected to the English test. After that English test was applied and assessed out of 1200 points. Interview score of the 1. candidate was higher than the score of 4. candidate. It was because of the assessment score in respect to the business knowledge criteria. In contrast, open communication assessment score of the 4. candidate was higher than

the 1. candidate. But the English exam score of 4. candidate was higher. In this context, the human resource department considered that business knowledge could be improved in the course of time. Therefore 4. candidate was preferred for the proposed position.

Table 2. Comparison of Fuzzy Logic Techniques with Decision of Decision Makers

Interview Scores	Real Interview	Mamdani with 127 rules	ANFIS with 243 rules
1. Candidate	93.75	94.20	94.05
4. Candidate	87.50	88.01	87.92
English Test Score	Real Interview	Mamdani	ANFIS
1. Candidate	584	584	584
4. Candidate	650	650	650
Last Decision	4. Candidate	4. Candidate	4. Candidate

In addition to these selection steps, mamdani and anfis models have evaluated the 1. and 4. candidates and scored 94,20 and 94,05 points for them respectively. Other candidates were eliminated as a result of the real interview. English test scores of the two candidates were given to program to learn their scores. So convergence of the models to real selection was resulted in the last decision as 4. candidate. When the mamdani and anfis type models were compared, first interview scores of 1. and 4. candidates are close to each other. Moreover, real scores and 116 rules differences were appeared in models. Prediction results of 1. candidate are %99.5 and %99.6, results of 4. candidate are %99.4 and %99.5 for the first interview of mandani and anfis respectively. Consequently, sugeno type-1 Anfis model with a very small prediction margin is more useful for proposed selection than mamdani type fuzzy model. In mamdani model these 127 rules were written one by one according to criteria weights of the decision makers. 243 rules used in anfis model were determined automatically by anfis toolbox of the MATLAB by using mamdani data base. The adaptive capability of the anfis model depends on its neural network base and assures future prediction about human resource selection. This capability can be tested by changing criteria weights of selection process.

5 Conclusion

This paper presents mamdani and sugeno type fuzzy inference system modeling techniques being used while group decision making in the fuzzy environment and displays the methods process with an empirical application. For this purpose, as decision makers, two top managers (human resource manager and plant manager) in a business organization that is in the list of First 500 Big Industrial Organizations of Turkey has evaluated decision criteria and the candidates by using linguistic variables for the position of mechanical maintenance manager. These verbal data have been transformed into triangular fuzzy numbers for mamdani model and also triangular type membership functions have been used to constitute both mamdani and sugeno type-1 fuzzy inference systems. According to the models, the candidates have been ranked from the best to the worst with respect to the calculated closeness coefficients. Mamdani and sugeno type fuzzy decision making models have been obtained by using fuzzy logic and ANFIS toolboxes of MATLAB software respectively and their applications on process have been realized via Simulink/MATLAB. All obtained prediction results have been compared with table according to modeling performances of used techniques. This study shows that for deciding more accurately and effectively in the human resource selection process, various fuzzy logic models are considerably suitable as an approach of fuzzy multi-criteria group decision making. Two aspects of this study that can contribute to the literature have been considered. Firstly, in the literature to date there isn't any investigation predicting the most appropriate candidate for the machine maintenance manager position by using these two methods and comparing the results of them. Therefore this study investigates the applicability of two fuzzy logic methods for predicting the aforementioned selection process and it defines which method is more useful with comparing rule tables. Secondly, expert systems such as fuzzy logic can bring a new insight to human resource selection process which has great importance for the organizations and also affects the future performance of them. More effective decisions can be available with such fuzzy modeling techniques.

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