Designing a Multi-Purpose Fuzzy Model for Human Resource Management in Production Systems

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ABSTRACT
In today's industrialized world, production is one of the key pillars of the country's progress and plays a decisive role in the economy of nations. Proper management of production systems can dramatically increase system productivity and create a good economic benefit for the manufacturing system. Human resources are one of the most important sources in each production system that play an important role in the productivity and efficiency of the production system. Also, human resources can boost other resources in a production system. So human resource management is very important and necessary. In this paper, a multifunctional fuzzy model for human resource management in production systems is presented. This multi-purpose fuzzy model has been implemented by MATLAB software and the results have been implemented on a real production system.

Keywords
Production Systems, Human Resources, Fuzzy Model, Productivity

1. INTRODUCTION
In the contemporary world, although human beings have moved from the age of industry to the age of communication, production has always been regarded as an important part of the global economy. Production and industry in the current world play a vital and important role in the lives of human societies. Today, manufacturing systems are constantly changing as they face the competitive environment and high expectations of their customers. Modern and advanced high-tech manufacturing systems (such as automotive, aerospace and electronics) are very complicated. The complexity of modern production systems depends on several factors, such as: multiple production processes, highly advanced equipment, batch processing and human resources management. The complexity of production systems, as well as the high cost of setting up and maintaining such systems, require formal models and deductive models. In fact, the current complex production systems cannot be set up solely on the basis of previous experience and principles and kept in the competitive cycle.

A production system is the method of locating and operating machines, tools, materials, humans and information to produce a physical product or service. There should be a pricing feature with specific parameters for products produced by a system. In general, production systems have different challenges, among which the most important ones are process control [1], scheduling [2], energy consumption management [3], flexibility [4], and human resource management [5]. The main purpose of this paper is to investigate human resources management of production systems. Human resource management is the performance improvement of production systems through individual employee performance. Human resource management has several aspects, among which the most important ones are recruitment and selection, planning for labor forces, increasing motivation for performance improvement, talent management, and encouraging approaches [5]. So far, several definitions have been proposed for human resource management that some of the most important ones are listed in Table 1.

Table 1 Definitions of Human Resource Management

	researchers	definition
1	Boxall [6]	Key strategy and integrated approach to hiring staff, expanding staff and increasing staff welfare
2	Watson [7]	Activities related to the management of staff recruitment and the relations governing it in production systems
3	Armstrong [8]	A coherent and comprehensive approach to hiring and expanding staff in manufacturing systems
4	Holbeche [9]	Identify all employee incentives and efforts to meet staffing needs

Talent management is one of the most important and essential aspects of human resource management in manufacturing systems. Talent managementis a term that was first introduced by Michaels and colleagues in the 1990s and in an article titled War on Talents [10]. Subsequently, many researchers identified talent management as an important and influential factor in the success of production systems, which can create a competitive advantage for a company by identifying, developing and attracting talented employees. For example, in 2006, researchers at the Private Institute for Personnel and Development conducted a study in which 90% of respondents believed that talent management could have a positive impact on the company's activities, and more than half of them believed that almost all things are in the talent management circle [11]. As defined by Caratp, the concept of talent management is presented to reduce the gap between existing productivity and the required productivity of a production system. According to this definition, talent management is a kind of awareness and a tool for human resource management [5]. Also, according to the definition provided by Anwar, talent management is one of the key aspects of human resource management that studies various human resource aspects. According to this definition, the use of talented individuals is a mental and emotional relationship which an employee has with his/her career, system, manager, and colleagues [12]. This paper tries to get a high productivity, focusing on talent management of human resources in a production system. To achieve this goal, a multi-functional fuzzy intelligent model is presented.

This article is organized in five sections. In the second part, a review of the works done in the field of human resource management will be presented. In the third section, a multi-functional fuzzy model will be presented for human resource management in a production system. In Section 4, we will implement and evaluate the proposed method, and finally, in the fifth part, the conclusions will be presented.

2. RELATED WORKS

Huang et al. (2001) presented a neural network-based model for talent management in production systems [13]. This method tries to explore and extract management talent of the staff. Assessing employee management talent in different production systems varies according to production culture, leadership style and competitive environment. With the study of a specific production system, this method attempts to help choosing effective factors in the field of managerial talent in the system. To achieve this goal, the neural network was used to manage and discover talent in a production system. The neural network designed in this paper has six input variables and an output variable. Six variables were considered as inputs of the neural network: capabilities attributes, motivational traits, personality traits, perceptual skills, individual skills and technical skills. Also, the efficiency of one person's management talents was considered as the only output of this neural network. Eventually, the researchers succeeded in developing a software based on this model, which was designed to explore the management talent of the production system staff.

Jonathan et al. (2010) presented a classification algorithm for predicting employee talent in human resource management [14]. One of the challenges that human resources professionals are involved in is managing talent in the production system. In fact, ensuring that a suitable person at the right time is assigned to a job is a necessity for a production system. Prediction of employee talent is a good way to answer this question. So, categorization and prediction as data mining concepts can also be implemented on talent management. In this method, the decomposition decision tree has been used to predict the available talent in human resources. Johnston et al. used the knowledge gained from the production system databases to extract a talent performance model in the production system, drawing them in the tree structure. They considered six attributes as the input variables of the decision tree. In fact, six characteristics were considered as inputs to the decision tree: career (professional staff, support staff); gender; degree; work efficiency, knowledge and skills; individual characteristics, organizational activities and contributions; and assessment scores. Also, the answer to the question of whether the employee should be promoted is considered as the output of this classifier.

In 2013, Aksakal and colleagues introduced a new method for selecting employees in a production system based on talent management [15]. In this research, a model for employee selection process is presented based on talent management. The proposed method consists of three main steps. In the first step, there are six different criteria for selecting employees: communication, decision-making power, teamworking, leadership, individual skills and techniques. These criteria were considered as the main criteria for decision making. In the second step, the six criteria were weighted by an algorithm called DEMATEL. The DEMATEL algorithm is such that it can convert behavior between criteria into an intelligent structural model and assign weights to criteria. The results of the implementation showed that three criteria are more important: leadership, teamworking, and decision-making power. Finally, in the third step, the candidates were compared and ranked according to the six weighting criteria.

In 2015, Caratp et al. Presented a fuzzy logic-based approach for talent management in production systems [5]. Various studies have shown that talent management is an inaccurate category, and therefore fuzzy logic can be used to define and model it. Therefore, in this research, a fuzzy system with fuzzy maker and non-fuzzy maker is used to manage talent in production systems. This fuzzy system has seven input variables and two output variables. Based on these seven input variables, the if-then fuzzy rules were designed and, based on these rules, the output of the fuzzy system was determined. In fuzzy design, 65 fuzzy rules have been defined, in which the values of the output variables in these rules are determined based on the lingual values of the input variables.

Volchamy et al., In 2016, used fuzzy relations mappings to provide a talent management model for human resource management [16]. That research attempted to use fuzzy relations mapping to provide a guide for expert human resource managers in order to manage the talent in their organizations in an appropriate and proper manner. In the proposed method, two groups of nodes were defined: domain nodes and range nodes. Domain nodes represent the goals of talent management, while the range nodes represent the outputs of the production system. In this study, researchers investigated 21 different production systems for obtaining domain and range nodes. As a result of these studies, 18 nodes in the domain and 12 nodes in the range were defined. In the fuzzy relations mapping, the connection between domain nodes and range nodes is established. The fuzzy relations between domain nodes and range nodes is mapped on a fuzzy matrix with values 0 and 1. Experienced human resource managers can manage the talent in production systems with this fuzzy matrix.

3. SUGGESTED METHOD

In this section, a multifunctional fuzzy model for human resource management in production systems will be presented.

This fuzzy model consists of four phases: fuzzy maker, rule evaluation, rule aggregation, and non-fuzzy maker. Figure 1 shows the general schematic of this multipurpose fuzzy model.

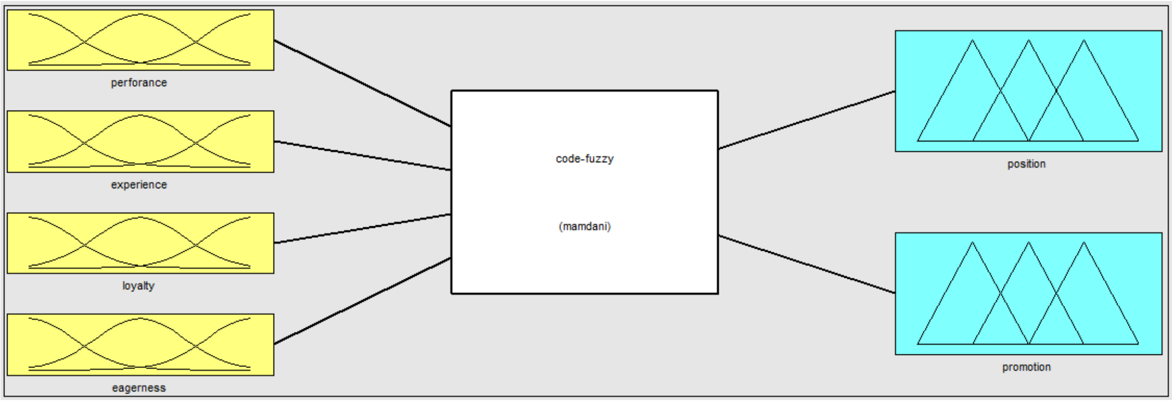


Figure 1 Multi-objective fuzzy model overview

3.1 Fuzzy maker

The fuzzy model has four lingual variables: efficiency, work history, loyalty and interest. Table 2 shows the values assigned to fuzzy model inputs. In this fuzzy model, different values are assigned to each of the input variables. Triangular and trapezoidal membership functions have also been used to define input variables. The membership functions of the input variables are shown in Fig. 2.

Table 2 values assigned to fuzzy model inputs

input	membership functions values		
efficiency	low	medium	high
work history	low	medium	high
loyalty	little	medium	large
interest	little	medium	large

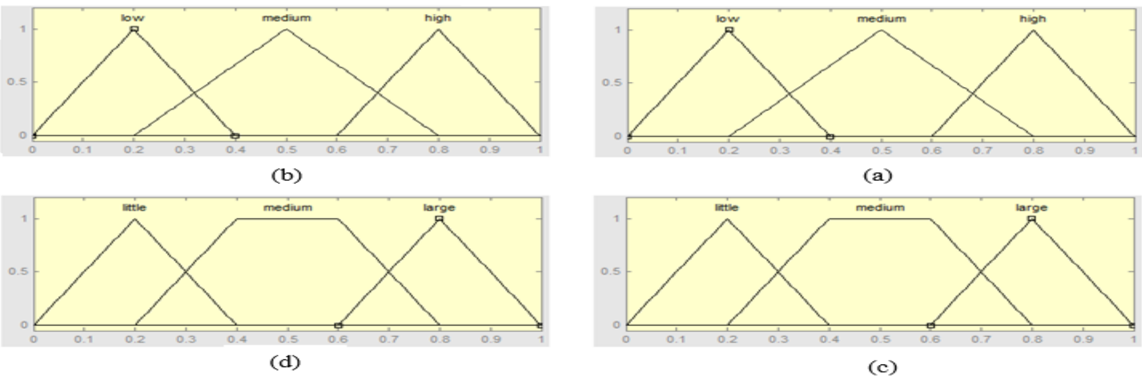


Figure 2 Membership functions of input variables (a) efficiency (b) work history (c) loyalty (d) interest

3.2 Evaluation of The Rules

In this section, fuzzy rules are evaluated. Given that three different lingual values are assigned to each of the four input variables, the total number of fuzzy rules in this multifunctional fuzzy model is 81. In other words, in this fuzzy model, all possible fuzzy rules are considered. In Table 3, some fuzzy rules are expressed

Table 3 Some fuzzy rules

efficiency	work history	loyalty	interest	job position	rank upgrade
low	*low*	*little*	*little*	*low*	*late*
low	*low*	*large*	*large*	*low*	*late*
low	*medium*	*little*	*little*	*low*	*late*
low	*medium*	*large*	*medium*	*low*	*late*
low	*high*	*little*	*little*	*low*	*medium*
low	*high*	*medium*	*large*	*low*	*medium*
medium	*low*	*little*	*little*	*medium*	*late*
medium	*low*	*large*	*large*	*medium*	*late*
medium	*medium*	*little*	*medium*	*medium*	*medium*
medium	*medium*	*large*	*medium*	*medium*	*medium*
medium	*high*	*little*	*medium*	*medium*	*soon*
medium	*high*	*medium*	*large*	*medium*	*soon*
high	*low*	*medium*	*little*	*medium*	*medium*
high	*low*	*large*	*little*	*medium*	*medium*
high	*medium*	*medium*	*little*	*high*	*soon*
high	*medium*	*large*	*little*	*high*	*soon*
high	*medium*	*large*	*medium*	*Very high*	*soon*
high	*high*	*little*	*little*	*Very high*	*soon*
high	*high*	*medium*	*medium*	*Very high*	*soon*

3.3 This Aggregation of Rules

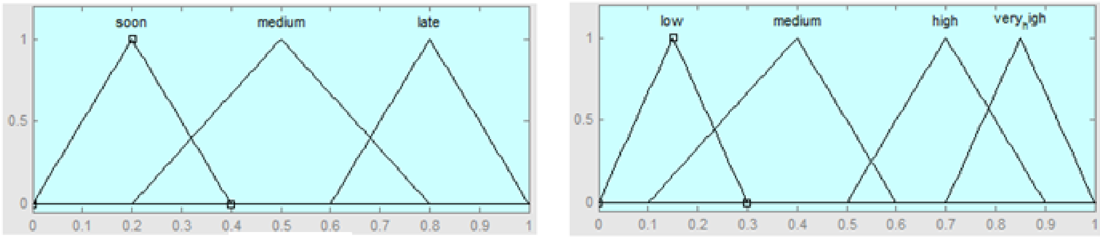
As it is obvious, this fuzzy model has two lingual variables: job position and rank upgrade. These variables are outputs of the model. The lingual variable of the job position has four modes and the lingual variable of rank upgrade has three modes. In this fuzzy model, each of the lingual variable modes of the job position represents a job class in a production system. Job classes equivalent to lingual variables modes of job positions are shown in Table 4.

Table 4 job class equivalent to job position mode

job position mode	job class
low	*worker*
medium	*Foreman*
high	*Engineer*

Very high	*manager*

As mentioned, this fuzzy model has two output variables. Triangular membership functions have been used to define the output variables. The membership functions of variables of job position and rank upgrade are shown in Figure 3.



(b) (a)

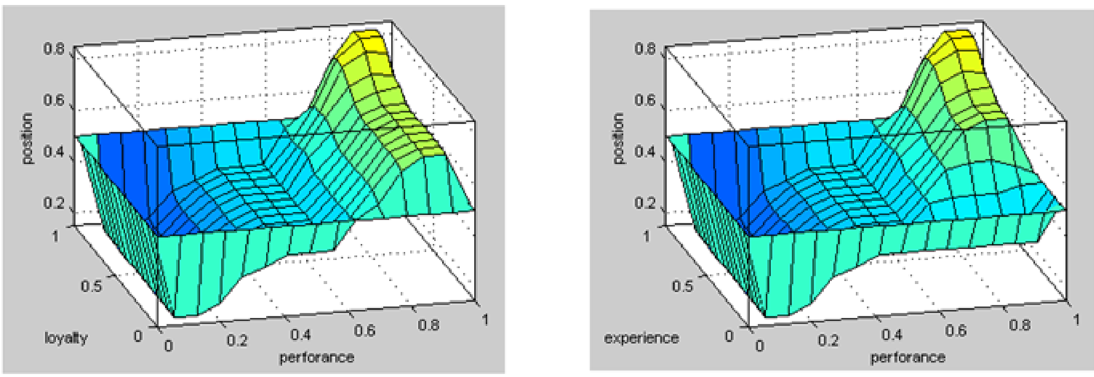
Figure 3 The membership functions of the output variables (a) job position (b) rank upgrade

3.4 Defuzzification

The Defuzzification stage is the last phase of the fuzzy model. Two numerical values are produced at this stage, indicating the job position and rank upgrade. The center of gravity technique is used to calculate these numerical values in the Defuzzification stage. In this fuzzy model, Sigma method is used to perform Defuzzification.

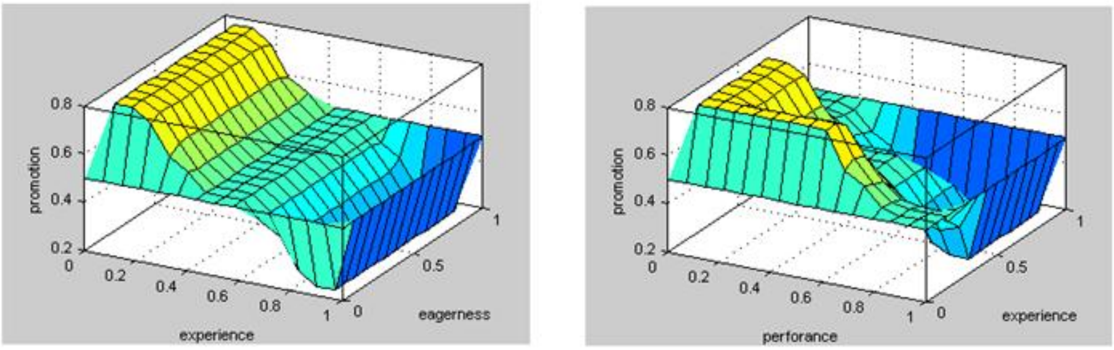
4. Methodology Evaluation

This multipurpose fuzzy model has four input variables and two output variables. Output variables are directly dependent on the input variables. The effect level of input variables on output variables is determined by fuzzy rules. The effect condition of input variables of efficiency, work background and loyalty on variable of job position is shown in Figure 4. As shown in Fig. 4, the input variable of performance has a great influence on the output variable of the job position. Figure 5 also shows how the inputs variables of performance; work background and interest affect the variable of rank upgrade. As shown in Figure 5, the input variable of the work background has a great influence on the output variable of rank upgrade.



(b) (a)

Figure 4 Effect of input variables on job position variable (a) Effect of efficiency and work history (b) Effect of efficiency and loyalty



(b) (a)

Figure 5 Effect of input variables on the rank upgrade variable (a) Effect of efficiency and work history (b) Effect of work history and interest

To operate this fuzzy model, this model was implemented on Sari's Tajan Polymer Manufacturing System. The purpose of fuzzy model study on this system is to examine the job situation and the need for personnel's rank promotion. In fact, in this case study, we try to manage the talents of personnel using this fuzzy model in order to make the best use of human resources. 74 people are engaged as personnel in this production system. Of the personnel employed, there are 52 workers, 11 worker, 8 engineers and 3 managers. According to field studies on the personnel of this manufacturing system, the lingual values of the input variables of efficiency, work background, loyalty and interest have been gathered. In other words, the experts have been used for the collection of data from the personnel of this system, which is the top management of the production system. Based on the lingual values for the input variables, this fuzzy model was implemented to identify job positions and ranks upgrade of the personnel. Regarding the outputs of the fuzzy model and comparing the current status of the personnel in the production system in question, it seems that the manufacturing system has a precision of 92% in the matter of personnel's job positions. Also, this manufacturing system has a precision of 53% in the matter of personnel's rank upgrade. For example, in a survey of workers in the manufacturing system, 49 out of the 52 existing workers are well-suited to work. However, out of the 52 existing workers, only 25 workers are well rank upgraded. In general, it can be said that given the results of this fuzzy model, this system should pay more attention to the characteristics of the rank upgrade of its personnel, in order to increase the efficiency and yield of human resources.

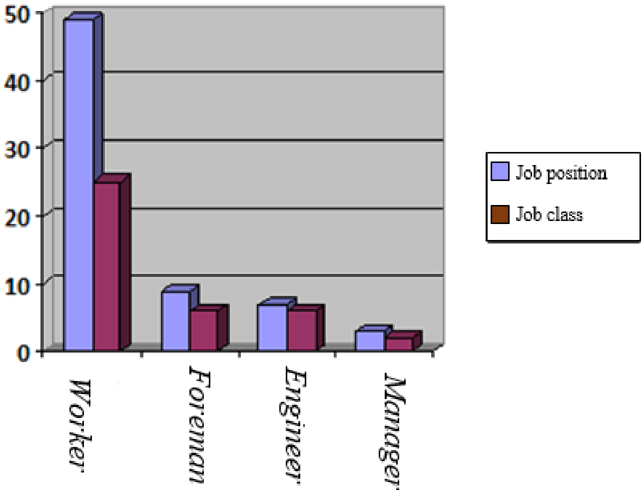


Figure 6 Precision of the production system of polymeric materials in the job position and personnel rank upgrade

5. CONCLUSION AND RESULTS

A multifunctional fuzzy model for human resource management in manufacturing systems was presented in this paper. This fuzzy model has four variables: efficiency, work background, loyalty and interest. These variables are input to the model. The model also has two output variables: job status and rank upgrade. After designing a multi-purpose fuzzy model in MATLAB software, this model was studied and investigated on a real production system. As a suggestion for future works, input variables of the fuzzy system can be selected with the help of an optimization algorithm.

6. REFERENCES

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