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Competency-based selection and assignment of human resources to construction projects

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ANFIS.

Abstract As part of human resource management policies and practices, construction firms need to define competency requirements for project staff, and recruit the necessary team for completion of project assignments. Traditionally, potential candidates are interviewed and the most qualified are selected. Precise computing models, which could take various candidate competencies into consideration and then pinpoint the most qualified person with a high degree of accuracy, would be beneficial. This paper presents a fuzzy adaptive decision making model for selection of different types of competent personnel. For this purpose, human resources are classified into four types of main personnel: Project Manager, Engineer, Technician, and Laborer. Then the competency criteria model of each main personnel is developed. Decision making is performed in two stages: a fuzzy Analytic Hierarchy Process (AHP) for evaluating the competency criteria, and an Adaptive Neuro-Fuzzy Inference System (ANFIS) for establishing competency IF-THEN rules of the fuzzy inference system. Finally, a hybrid learning algorithm is used to train the system. The proposed model integrates a fuzzy logic qualitative approach and neural network adaptive capabilities to evaluate and rank construction personnel based on their competency. Results from this system in personnel staffing show the high capability of the model in making a high quality personnel selection.

1. Introduction

Human Resource Management (HRM) is defined by the processes that organize, manage and lead a project team [1]. It contributes to the success of the project [2,3] and creates a competitive advantage for the organization [4,5]. HRM policies, processes and practices in a construction company are in some ways supportive of project-oriented work and are different from more traditional HRM processes and practices [6], which are designed for a classically-managed organization, where the emphasis is not on projects but instead on routine products and services, and where job requirements are well defined and stable [7].

Performance improvement is a fundamental concern of management [8,9]. Various factors affect the performance of projects, which include human-related factors, project-related factors, project procedures, project management actions and external environments [10,11]. Yang et al. [12] indicated that teamwork has a statistically significant influence on project performance. Guest and Neil [13] found an association between HRM and workplace performance, and also between employee attitudes and workplace performance. Belout and Gauvreau [14] state that based on correlation analysis, HRM has an impact on project performance. Pfeffer [15] argued persuasively that companies which understand the relationship between people and organizational performance are those that usually win out in the long run. Therefore, improvement in the performance of the project, program, portfolio and organization is correlated to improvement in the performance of staff.

The project team is comprised of appropriate people with assigned roles and responsibilities for completing the project [1]. Project team members may also be referred to as project staff or personnel [1,7]. Developing the project team improves people skills, technical competencies, and overall team environment and project performance [16]. Thus developing effective project teams is a critical factor for project success [17,18].

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Effective team development strategies and activities are expected to increase team performance, which increases the likelihood of meeting project objectives [19]. The degree or extent of this impact may vary, depending on certain factors, such as project type, characteristic and organizational context. If project team members do not possess the required competency, performance can be jeopardized [1]. Competency is the knowledge, skill and behavior a person needs to fulfill his/her role [20]. Assessing competency, skills and abilities, and knowing personality traits and the key behavior of individuals increase the chances of choosing a team that has the potential for success [16].

Traditionally, an expert — for example the chief officer of the human resource department of a company — interviews the candidates for positions and after analyzing each person's capabilities selects the best. The statistical techniques approach supports the engaging decision through the arrangement of test scores and the measure of accomplishment for the candidate [21]. However, the process is often ambiguous, biased and lacking in accuracy [22].

2. Research objectives

As part of HRM policies and practices, construction firms need to define the competency requirements for all project personnel, and obtain the team necessary to complete project assignments. Therefore, the purpose of this research is to construct and put into practice a competency-based model for the selection and assignment of construction project personnel, which are classified into four types: Project Manager, Engineer, Technician and Laborer. A survey was undertaken to develop the competency criteria model of each main personnel. By consideration of main personnel competency, we develop a two-stage model representing complete project staff evaluations. The model is trained with a number of actual data taken with a series of interviews. Moreover, statistical analysis of model output and traditional interview-based data is performed.

3. Literature review

The contemporary employee selection is a complex decision making process that has the capability of placing the correct employees in the right jobs at the right time. This process has a multi-hierarchical structure that solves the challenging task of a decision making process. The Analytic Hierarchy Process (AHP) usually uses a multi-hierarchical structure. The AHP is a process-based on the theory of constructing hierarchies and setting priorities with reasonable consistency [23]. Lai [24] described the employee selection process as a multi-objective decision making problem. Iwamura and Lin [25] explained that the employee selection process requires the accomplishment and aggregation of different factors. Labib et al. [26] suggested an employee selection process that uses the AHP and has four stages.

Other contemporary methods in employee selection are artificial intelligence techniques. Over the last twenty five years, many real-world problems, including employee selection, have been solved with fuzzy sets and logic. Lazarevic [27] presented a two-level employee selection fuzzy model to minimize subjective judgment in the process of distinguishing between an appropriate and inappropriate employee for a job position. Golec and Kahya [28] presented a comprehensive hierarchical structure for selecting and evaluating the right employee. The study structure can systematically build the goals of employee selection to carry out the business goals and strategies of an organization, and set up a consistent evaluation standard for facilitating a decision process. The process of matching an employee with a certain job is performed through a fuzzy model. Korkmaz et al. [29] presented an AHP and a two-sided matching-based Decision Support System (DSS) to assist detailers. The DSS is programmed to generate position preferences from position requirement profiles and personnel competence profiles using AHP, and matches personnel to positions by using two-sided matching. Polychroniou and Giannikos [30] presented a fuzzy multi criteria decision making methodology for selecting employees. The methodology is based on the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) multi criteria decision tool, and the algorithm presented by Karsak and Slocum [31]. Kelemenis and Askounis [32] also presented a fuzzy TOPSIS for the ranking of personnel alternatives. Lin [33] develops a job placement intervention by taking into account fuzzy assessment and a mixed integer programming model to fulfill the efficient fit from the right policy. Gungor et al. [34] proposed a personnel selection system based on fuzzy AHP. The fuzzy AHP is applied to evaluate the best adequate personnel dealing with the ratings of both qualitative and quantitative criteria. Drigas et al. [35] presented an expert system using Neuro-Fuzzy techniques, which investigates a corporate database of unemployed and enterprise profile data for evaluation of the unemployed in certain job positions. This study uses a Sugeno type Neuro-Fuzzy inferences system for matching an unemployed with a job position.

As seen in existing studies, there are two problems: the decision making hierarchy for selection, and the methodology to be used. The former employee selection problem studies are from developed decision making criteria, based on job analysis. In addition, competency criteria hierarchies that are studied in literature are for general employees, and construction project personnel are not specifically investigated.

One of the methods for solving these problems could be AHP. But based on human experience and judgment, which are represented by linguistics and vague patterns, the AHP approach may contribute to imprecise judgment by decision makers [36]. Therefore, a much better representation of these linguistics can be developed as quantitative data. This type of data set is then refined by the evaluation methods of fuzzy set theory. Many researchers have provided evidence that fuzzy AHP is relatively more efficient than the AHP method [36]. In spite of the Gungor et al. [34] research methodology, factors need to be trained and checked, based on actual employee evaluated data due to system validity.

The other method of solving these problems could be expert system modeling, which is presented in the form of a rule-base and consists of three blocks: input, inference and output. In fuzzy rule-base modeling, the results are affected from the type of membership function and expert knowledge. Although Drigas et al. [35] used a neuro-fuzzy inference system to select and assign an employee to a job position, the fuzzy inference system that uses fuzzy clustering methods to identify the structure of the model based on actual employee evaluated data is more reliable [37].

4. Methodology

In the current study, a hierarchical structure is constructed and a fuzzy adaptive model is employed to select the most

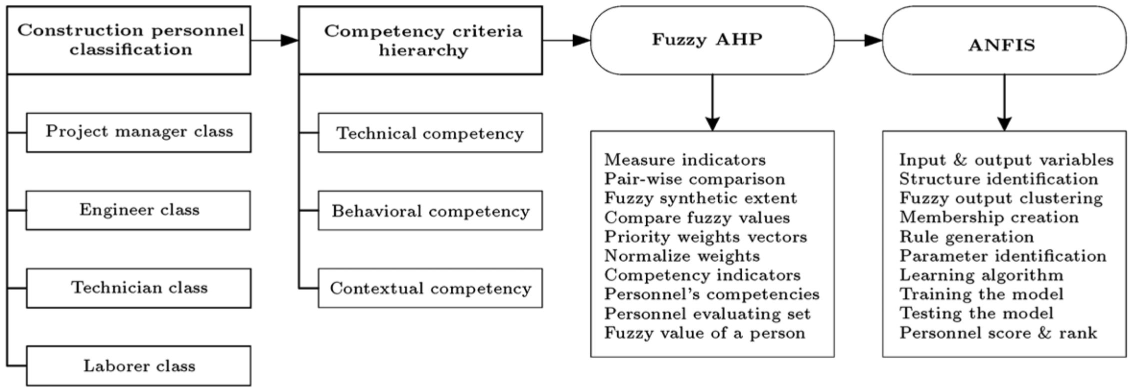

Figure 1: Flowchart of personnel selection method.

competent construction personnel. To prepare this decision support system, some initial steps must be taken: First, human resources are classified into four main personnel: Project Manager, Engineer, Technician and Laborer. A set of three main competency criteria for each personnel class is determined and sub factors are explored through a literature review. A questionnaire survey was utilized to evaluate the traditional interview-based importance index of each factor, and to reject unimportant factors. Then from data collected through several interviews, a series of pair wise comparisons for each personnel class is performed, using fuzzy AHP for evaluating fuzzy important indicators of competency criteria. Afterwards, since the fuzzy system function requires many parameters, the aforementioned parameters are improved through innovative computing techniques, including artificial neural networks, which combine with the fuzzy inference system. The current study, however, determines the structure of the model using the fuzzy c-mean clustering method, based on actual employee evaluated data. Moreover, a hybrid learning algorithm is used to train the system. When the final model is ready, its prediction accuracy is checked by using a set of actual data taken with a series of interviews. Finally, statistical analysis of model outputs and the traditional interview-based data are performed. Its utilization method is then shown in relation to real-life construction personnel selection, and eventually some of its potential uses within the construction industry are presented. Figure 1 illustrates a flowchart for the personnel selection procedure.

5. Main personnel classification

The main personnel of construction projects, according to UDL/ETA [38], are classified as follows: Project manager, Engineer, Technician and Laborer. The process for classifying main personnel to determine the competency development framework includes such steps which are as follows.

5.1. Describtion of main personnel occupations

To describe main occupations and clarify their tasks and job zone, a brief description of 'main personnel' is mentioned below: A project manager is the person accountable for accomplishing the stated project objectives. Key project management responsibilities include creation of clear and attainable project objectives, building project requirements and managing the triple constraints for projects, which are cost, time and quality [1]. An engineer is a person who has a profession in which a knowledge of mathematical and physical sciences gained by study, experience and practice is applied with judgment to develop ways to utilize, economically, the materials and forces of nature for the progressive well-being of humanity in creating, improving and protecting the environment and in providing structures for the use of humanity [39]. A technician is a person who applies the theory and principles of engineering in the planning, designing and overseeing production, construction and maintenance of industries and facilities under the direction of engineering staff or the project manager [38]. A laborer is a person who performs tasks involving physical labor in industry, service or construction projects, and may operate hand and power tools of all types, clean and prepare sites or simply assist other craft workers [38].

5.2. Evaluation of the employee best class suit

To suit an employee to a proper class, employees or candidates are evaluated on the basis of their resumes. A resume is a written document that is intended to convince an employer that his needs and the skills and qualifications of the applicant are a perfect match. It usually includes professional experience, special skills, education and accomplishments.

5.3. Validity of the employee selection

An interview may be the only means employed for the evaluation of selection, or it may form one stage in a sequence of eliminating impediments. These include competency evaluations, as well as health checks, education information, references, etc. Correct evaluation is therefore of crucial importance, and must mean that both parties to the evaluation decision, interviewer and it interviewee, are satisfied, and so the right decision has been made.

6. Developing competency criteria hierarchy

Competency is a cluster of related knowledge, attitudes, skills and personal characteristics that [40]:

- Affect a major part of one's job;
- Correlate with performance on the job;
- Can be measured against well-accepted standards;
- Can be improved via training and development;
- Can be broken down into dimensions of competence.

At this stage, competency-based factors for each class are presented according to the selection system.

Table 1: Project manager competency criteria analysis.

	Technical competencies	Number of Scoring							
		5	4	3	2	1	MS	RII	NII%
C_1	Project management success	6	14	6	3	1	3.70	0.74	4.83
C_2	Interested parties	13	15	2	0	0	4.37	0.87	5.65
C_3	Project requirements	9	9	7	4	1	3.70	0.74	4.80
C_4	Risk & opportunity	6	11	7	5	1	3.53	0.71	4.59
C_5	Quality	6	9	9	5	1	3.47	0.69	4.49
C_6	Project organization	7	10	7	6	0	3.60	0.72	4.68
C_7	Teamwork	15	9	6	0	0	4.30	0.86	5.59
C_8	Problem resolution	5	16	8	1	0	3.83	0.77	5.03
C_9	Project structures	1	6	10	10	3	2.73	0.55	3.64
C_{10}	Scope & deliverables	8	9	10	3	0	3.73	0.75	4.92
C_{11}	Time & project phases	16	14	0	0	0	4.53	0.91	5.95
C_{12}	Resources	12	10	8	0	0	4.13	0.83	5.49
C_{13}	Cost & finance	16	13	1	0	0	4.50	0.90	5.97
C_{14}	Procurement & contract	9	10	9	2	0	3.87	0.77	5.18
C_{15}	Changes	6	8	15	1	0	3.63	0.73	4.89
C_{16}	Control & reports	8	11	8	3	0	3.80	0.76	5.08
C_{17}	Information & documentation	9	10	8	3	0	3.83	0.77	5.13
C_{18}	Communication	9	10	9	2	0	3.87	0.77	5.25
C_{19}	Start-up	9	9	7	4	1	3.70	0.74	5.05
C_{20}	Close-out	9	9	7	4	1	3.70	0.74	5.05
	Behavioral competencies	Number of scoring							
		5	4	3	2	1	MS	RII	NII%
C_1	Leadership	14	16	0	0	0	4.47	0.89	8.00
C_2	Engagement & motivation	10	13	7	0	0	4.10	0.82	7.44
C_3	Self-control	6	10	11	3	0	3.63	0.73	6.76
C_4	Assertiveness	5	13	12	0	0	3.77	0.75	7.01
C_5	Relaxation	3	8	12	5	2	3.17	0.63	5.95
C_6	Openness	4	12	13	1	0	3.63	0.73	6.75
C_7	Creativity	4	12	13	1	0	3.63	0.73	6.84
C_8	Results orientation	1	4	13	8	3	2.72	0.54	5.12
C_9	Efficiency	3	10	15	2	0	3.47	0.69	6.33
C_{10}	Consultation	10	12	8	0	0	4.07	0.81	7.37
C_{11}	Negotiation	7	10	9	3	1	3.63	0.73	6.63
C_{12}	Conflict & crisis	9	16	5	0	0	4.13	0.83	7.52
C_{13}	Reliability	11	8	6	4	1	3.80	0.76	7.48
C_{14}	Values appreciation	5	11	10	2	2	3.50	0.70	7.44
C_{15}	Ethics	9	16	5	0	0	4.13	0.83	8.57
	Contextual competencies	Number of scoring							
		5	4	3	2	1	MS	RII	NII%
C_1	Project orientation	8	10	8	3	1	3.70	0.74	9.39
C_2	Programme orientation	1	4	15	7	3	2.77	0.55	7.75
C_3	Portfolio orientation	7	13	3	5	2	3.60	0.72	10.93
C_4	PPP implementation	5	7	13	2	3	3.30	0.66	9.70
C_5	Permanent organization	8	11	7	4	0	3.77	0.75	10.98
C_6	Business	0	5	17	7	1	2.87	0.57	8.12
C_7	Systems, products & technology	4	14	11	1	0	3.70	0.74	10.18
C_8	Personnel management	10	20	0	0	0	4.33	0.87	12.01
C_9	Health, safety & environment	5	16	9	0	0	3.87	0.77	11.16
C_{10}	Finance	6	12	8	4	0	3.67	0.73	10.73
C_{11}	Legal	8	11	10	0	1	3.83	0.77	10.88

6.1. Identify the competency criteria

Competency models are a highly useful tool to make sure that human resource systems facilitate and support the strategic objectives of a company. It increases the likelihood of placing the right people in the right job [41]. Because of inherent differences between the four main classes previously mentioned, their competency models are accordingly different. Therefore, four competency development models are established for the project manager, engineer, technician and laborer.

In order to determine the competency criteria hierarchy of construction personnel, three main factors of technical, behavioral and contextual competency, and their sub competency factors were identified through an extensive literature review and a series of interviews. Then for each main personnel class, a structured questionnaire was developed to gather expert opinions. There are two sections in the questionnaire. The first part is a brief introduction of the questionnaire. In the main body of the questionnaire, respondents were invited to evaluate sub competency factors listed in Tables 1–4, in terms of the importance level. The importance level is measured on a 5-point, Likert scale, where 5 denotes extreme importance, 4 is important, 3 is neutral, 2 is unimportant, and 1 is negligible. To ensure a better understanding of competency factors in the questionnaire, and to decrease the chance of misinterpretation, a brief explanation for some factors was provided. The questionnaire was then administered to 100 contractors randomly selected from Grade 1 building contractors in Tehran, Iran. We requested that the questionnaire be completed by a chief officer of the human resource department, or a senior professional within the orga-

Table 2: Engineer competency criteria analysis.

	Technical competencies	Number of scoring					MS	RII	NII%
		5	4	3	2	1			
C_1	Engineering practice	25	9	1	0	0	4.69	0.94	10.72
C_2	Engineering planning	7	9	17	2	0	3.60	0.72	8.39
C_3	Engineering design	27	8	0	0	0	4.77	0.95	11.01
C_4	Engineering operation	7	17	11	0	0	3.89	0.78	9.27
C_5	Determine systems	5	13	10	6	1	3.43	0.69	8.27
C_6	Investigation and reporting	1	5	23	2	4	2.91	0.58	7.07
C_7	Research and development	2	13	17	2	1	3.37	0.67	8.33
C_8	Defines resources	26	9	0	0	0	4.74	0.95	11.71
C_9	Estimate materials	18	9	8	0	0	4.29	0.86	10.92
C_{10}	Changes	6	9	19	1	0	3.57	0.71	9.11
C_{11}	Technical development	1	5	8	14	7	2.40	0.48	6.15
C_{12}	Technical promotion	0	2	7	17	9	2.06	0.41	5.17
	Behavioral competencies	Number of scoring							
		5	4	3	2	1	MS	RII	NII%
C_1	Cooperation	9	12	14	0	0	3.86	0.77	7.87
C_2	Commitment	13	12	9	1	0	4.06	0.81	8.33
C_3	Independence	5	7	19	3	1	3.34	0.67	7.04
C_4	Efficiency	3	11	19	2	0	3.43	0.69	7.30
C_5	Attention to detail	3	8	17	6	1	3.17	0.63	6.73
C_6	Coaching	0	2	6	23	4	2.17	0.43	4.52
C_7	Communication skills	2	16	12	4	1	3.40	0.68	6.78
C_9	Creativity	14	16	5	0	0	4.26	0.85	6.90
C_{10}	Initiative	5	15	9	6	2	3.41	0.68	8.55
C_{11}	Judgment	2	11	12	10	0	3.14	0.63	6.93
C_{12}	Teamwork	10	18	6	1	0	4.06	0.81	6.27
C_{13}	Values diversity	3	8	21	3	0	3.31	0.66	8.03
C_{14}	Ethics	9	14	12	0	0	3.91	0.78	7.13
	Contextual competencies	Number of scoring							
		5	4	3	2	1	MS	RII	NII%
C_1	Project orientation	9	10	10	4	2	3.57	0.71	9.10
C_2	Programme orientation	2	11	7	9	6	2.83	0.57	7.93
C_3	Portfolio orientation	3	4	15	9	4	2.80	0.56	8.03
C_4	PPP implementation	7	11	13	4	0	3.60	0.72	10.59
C_5	Self-management	11	16	8	0	0	4.09	0.82	12.77
C_6	Engineering project management	13	20	2	0	0	4.31	0.86	14.44
C_7	Environmental management	6	17	9	2	1	3.71	0.74	13.73
C_8	Systems & products	2	7	11	11	4	2.77	0.55	11.01
C_9	Personnel management	9	10	11	4	1	3.63	0.73	14.91
C_{10}	Health, security & safety	14	20	1	0	0	4.37	0.87	19.44
C_{11}	Legal	6	10	17	2	0	3.57	0.71	17.91

nization who would be able to form opinions from a more holistic viewpoint. The questionnaire was sent out in July 2009, and 30 valid responses for the project manager class and 35 valid responses for other personnel classes were returned at the end of September 2009. The response rate was 30% for the project manager class and 35% for other personnel classes, which appears to be a standard response rate for questionnaires.

The Mean Score (MS) for each factor is computed by the following formula:

$$\mathrm{MS} = \frac{\sum(f \times s)}{N}, \quad (0 \leq \mathrm{MS} \leq 5), \tag{1}$$

where s is score given to each factor by respondents; ranging from 1 to 5, where "1" is "not significant" and "5" is "extremely significant;" f is frequency of response to each rating (1-5), for each factor; and N is total number of respondents for that factor.

In addition to the MS, the five-point scale was transformed to Relative Importance Indices (RII), using the relative index ranking technique, to determine the ranking of the factors and verify the evaluation by the MS. The RII were calculated using the following formula:

$$\mathrm{RII} = \frac{\sum(f \times s)}{5 \times N}, \quad (0 \leq \mathrm{RII} \leq 1), \tag{2}$$

where the total point score is the summation of all ratings for a given factor, and 5 is the maximum rating possible. Competency criteria, the calculated RII of which were over 0.4, were rejected from competency development models. Moreover, Normalized Importance Indices (NII) were calculated to evaluate the traditional interview-based importance index of each person's competency.

Also considering that the questionnaire was completed by the senior staff members of top contractors, the response rate was considered satisfactory. A data examination was performed to test the internal consistency reliability of the 5-point Likert scale used in this survey. As supported by the literature, Cronbach's coefficient alpha was tested to determine internal consistency among competency. The coefficient alpha in this test is 0.91 for the project manager class, 0.89 for the engineer class, 0.90 for the technician class and 0.94 for the laborer class. All are near 1, showing a moderately high internal consistency of competency.

6.2. Project manager competency criteria hierarchy

When applied to project managers, competency can be described as consisting of three separate dimensions: technical,

Table 3: Technician competency criteria analysis.

	Technical competencies	Number of scoring							
		5	4	3	2	1	MS	RII	NII%
C_1	Technical practice	18	17	0	0	0	4.51	0.90	13.20
C_2	Technical planning	13	21	1	0	0	4.34	0.87	12.76
C_3	Technical design	5	12	14	4	0	3.51	0.70	10.66
C_4	Technical operation	13	19	3	0	0	4.29	0.86	13.25
C_5	Determine systems	5	9	18	3	0	3.46	0.69	10.67
C_6	Investigation and reporting	8	13	13	1	0	3.80	0.76	11.66
C_7	Research and development	1	8	21	4	1	3.11	0.62	9.64
C_8	Defines resources	5	7	18	5	0	3.34	0.67	10.19
C_9	Estimate materials	9	11	15	0	0	3.83	0.77	11.60
	Behavioral competencies	Number of scoring							
		5	4	3	2	1	MS	RII	NII%
C_1	Cooperation	16	15	4	0	0	4.34	0.87	11.13
C_2	Commitment	4	8	19	2	2	3.29	0.66	8.49
C_3	Dependability	2	3	19	11	0	2.89	0.58	7.33
C_4	Efficiency	17	13	5	0	0	4.34	0.87	10.80
C_5	Attention to detail	7	15	9	2	2	3.66	0.73	9.34
C_6	Adaptability	8	9	13	3	2	3.51	0.70	9.17
C_7	Analytical thinking	5	14	13	3	0	3.60	0.72	9.43
C_8	Persistence	9	8	11	7	0	3.54	0.71	9.32
C_9	Stress tolerance	4	13	18	0	0	3.60	0.72	9.50
C_{10}	Self control	2	1	10	15	7	2.31	0.46	6.22
C_{11}	Teamwork	10	13	12	0	0	3.94	0.79	10.65
	Contextual competencies	Number of scoring							
		5	4	3	2	1	MS	RII	NII%
C_1	Near vision	15	9	8	3	0	4.03	0.81	12.18
C_2	Oral comprehension	13	11	7	3	1	3.91	0.78	13.47
C_3	Oral expression	11	14	3	5	2	3.77	0.75	15.00
C_4	Deductive reasoning	6	7	15	5	2	3.29	0.66	14.22
C_5	Mathematical reasoning	1	5	19	7	3	2.83	0.57	12.99
C_6	Problem sensitivity	4	9	18	3	1	3.34	0.67	16.48
C_7	Visualization	5	13	10	6	1	3.43	0.69	18.15
C_8	Written comprehension	7	8	13	7	0	3.43	0.69	19.87
C_9	Health, safety & environment	1	9	15	6	4	2.91	0.58	18.65
C_{10}	Speech clarity	0	4	7	14	10	2.14	0.43	14.62

behavioral and contextual. For each dimension, according to the International Project Management Association [42], a competency criteria hierarchy was identified, describing which employee characteristic relates to which dimension. Table 1 shows the project manager competency criteria hierarchy analysis.

6.3. Engineer competency criteria hierarchy

Engineer competency is described as having three dimensions: technical, behavioral and contextual. According to UDL/ETA [38], ASCE [39], EA [43] and a series of interviews, the competency criteria hierarchy was identified. Table 2 shows the engineer competency criteria hierarchy analysis.

6.4. Technician competency criteria hierarchy

Compared to an engineer, a technician is generally someone in a technological field who has a relatively practical understanding of the general theoretical principles of that field. So, three dimensions of technician competency, technical, behavioral and contextual, were identified relatively as a practical engineer according to UDL/ETA [38], ASCE [39], EA [43] and a series of interviews. Table 3 shows the technician competency criteria hierarchy analysis.

6.5. Laborer competency criteria hierarchy

For the laborer, competence criteria are described for one who has three dimensions of competency, technical, behavioral and contextual. According to UDL/ETA [38] and a series of interviews, the competency criteria hierarchy was identified. Table 4 shows the laborer competency criteria hierarchy analysis.

7. Developing fuzzy AHP

The Fuzzy AHP method is a systematic approach to the alternative selection and justification problem, using the concepts of fuzzy set theory and hierarchical structure analysis. The decision maker can specify preferences in the form of natural language or numerical value, regarding the importance of each performance attribute. In the fuzzy AHP method, the pair-wise comparisons in the judgment matrix are fuzzy numbers, and use fuzzy arithmetic and fuzzy aggregation operators [44]. The procedure calculates a sequence of weight vectors that will be used to choose main attributes. Triangular fuzzy numbers were introduced into the conventional AHP in order to enhance the degree of judgment of the decision maker.

In the following, outlines of the developed analysis method on fuzzy AHP are given and are applied to a personnel selection problem. For easy computing, we summarize the algorithm for evaluating the personnel selection problem by fuzzy AHP.

Table 4: Laborer competency criteria analysis.

	Technical competencies	Number of scoring					MS	RII	NII%
		5	4	3	2	1			
C_1	Equipment selection	7	17	11	0	0	3.89	0.78	12.69
C_2	Instructing	18	13	2	2	0	4.34	0.87	13.84
C_3	Monitoring	11	16	8	0	0	4.09	0.82	13.50
C_4	Equipment maintenance	6	11	10	5	3	3.34	0.67	11.07
C_5	Learning strategies	3	4	9	8	11	2.43	0.49	7.78
C_6	Estimate materials	2	5	20	6	2	2.97	0.59	9.01
C_7	Critical thinking	4	19	8	3	1	3.63	0.73	10.74
C_8	Mathematics	0	2	14	12	7	2.31	0.46	6.63
C_9	Time management	4	16	13	2	0	3.63	0.73	9.97
	Behavioral competencies	Number of scoring							
		5	4	3	2	1	MS	RII	NII%
C_1	Attention to detail	22	13	0	0	0	4.63	0.93	11.23
C_2	Dependability	4	8	17	4	2	3.23	0.65	7.84
C_3	Self control	11	15	8	1	0	4.03	0.81	9.51
C_4	Cooperation	17	14	4	0	0	4.37	0.87	10.45
C_5	Stress tolerance	10	21	4	0	0	4.17	0.83	10.10
C_6	Initiative	7	17	9	1	1	3.80	0.76	9.43
C_7	Effort	25	10	0	0	0	4.71	0.94	11.82
C_8	Concern for others	15	8	6	3	3	3.83	0.77	10.05
C_9	Integrity	9	23	1	2	0	4.11	0.82	11.29
C_{10}	Teamwork	19	12	1	3	0	4.34	0.87	12.22
	Contextual competencies	Number of scoring							
		5	4	3	2	1	MS	RII	NII%
C_1	Manual dexterity	21	14	0	0	0	4.60	0.92	10.80
C_2	Multi-limb	13	22	0	0	0	4.37	0.87	11.50
C_3	Arm-hand	6	15	7	5	2	3.51	0.70	10.45
C_4	Static strength	6	19	9	1	0	3.86	0.77	12.05
C_5	Active listening	9	7	5	9	5	3.17	0.63	10.71
C_6	Coordination	5	13	10	4	3	3.37	0.67	12.08
C_7	Speaking	2	7	17	4	5	2.91	0.58	11.14
C_8	Oral comprehension	2	1	7	16	9	2.17	0.43	8.84
C_9	Control precision	8	11	3	7	6	3.29	0.65	13.52
C_{10}	Trunk strength	4	5	8	12	6	2.69	0.54	11.87
C_{11}	Near vision	3	8	20	3	1	3.26	0.65	14.96
C_{12}	Oral expression	4	2	7	13	9	2.38	0.48	11.86
C_{13}	Health, safety & environment	6	4	14	8	3	3.06	0.61	15.57

7.1. *Discover the measure indicators of every factor*

Employees can be assessed by observation during interviews. Therefore, we should determine the importance of competency indicators to measure whether or not the employee will be a good fit with the job. We use linguistic indicators to measure the employee with each factor. In applications, it is often convenient to work with Triangular Fuzzy Numbers (TFNs) because of their computational simplicity, and their use in promoting representation and information processing in a fuzzy environment. Triangular fuzzy numbers can be defined as a triplet (l, m, u). Parameters l, m and u, respectively, indicate the smallest possible value the most promising value and the largest possible value describing a fuzzy event [45].

There are various operations undertaken on triangular fuzzy numbers. But, here, only important operations used in this study are illustrated. If we define two positive triangular fuzzy numbers (l_1, m_1, u_1) and (l_2, m_2, u_2), then:

$$(l_1, m_1, u_1) \oplus (l_2, m_2, u_2) = (l_1 + l_2, m_1 + m_2, u_1 + u_2), \quad (3)$$

$$(l_1, m_1, u_1) \otimes (l_2, m_2, u_2) = (l_1 \cdot l_2, m_1 \cdot m_2, u_1 \cdot u_2), \quad (4)$$

$$(l_1, m_1, u_1)^{-1} \approx (1/u_1, 1/m_1, 1/l_1). \quad (5)$$

In this study, TFNs are adopted in the fuzzy AHP method. The linguistic competency importance sets for measure indicators for pair-wise comparisons are Not important, Weak important, Moderate important, Strong important and Extreme important. Figure 2 shows the membership function of linguistic variables, and Table 5 explains the numerical values of membership functions.

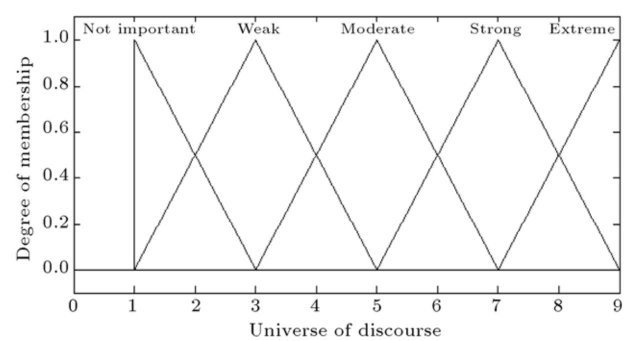

Figure 2: Membership functions for importance of measure indicators.

7.2. *Build fuzzy pair-wise comparison*

In this step, a comprehensive pair-wise comparison matrix is built by decision makers for competency measure indicators. This way, pair-wise comparison values are formed as linguistic TFNs according to a series of interviews. For example, we

Table 5: Numerical values for importance of the measure indicators.

Degree of importance	Linguistic variable	Positive TFN
$\tilde{1}$	Not important	(1, 1, 3)
$\tilde{3}$	Weak important	(1, 3, 5)
$\tilde{5}$	Moderate important	(3, 5, 7)
$\tilde{7}$	Strong important	(5, 7, 9)
$\tilde{9}$	Extreme important	(7, 9, 9)

present a fuzzy pair-wise comparison for the project manager class between technical competencies as shown in Table 6.

7.3. Define fuzzy synthetic extent

In this step, the fuzzy AHP introduced by Chang is utilized [46]. Let $C = \{C_1, C_2, C_3, \dots, C_n\}$ be the competency indicators set, and n be the number of competency criteria. Then for each competency measure indicator, an extent analysis is performed, respectively. Therefore, n extent analysis values for each competency can be obtained, with the following signs:

$$M_{C_i}^1, M_{C_i}^2, \dots, M_{C_i}^n, \quad i = 1, 2, \dots, n,$$

where all $M_{C_i}^j (j = 1, 2, \dots, n)$ are TFNs for the importance of measure indicators as shown in Figure 2. The steps of extent analysis can be given as in the following.

The value of the fuzzy synthetic extent, with respect to the ith competency indicator, is defined as:

$$S_i = \sum_{j=1}^{n} M_{C_i}^j \otimes \left[\sum_{i=1}^{n}\sum_{j=1}^{n} M_{C_i}^j\right]^{-1}, \tag{6}$$

where the symbol, $\otimes$, is element-by-element multiplication. To obtain $\sum_{j=1}^{n} M_{C_i}^j$, the fuzzy addition operation of n extent analysis values for a particular matrix is performed, such as:

$$\sum_{j=1}^{n} M_{C_i}^j = \left(\sum_{j=1}^{n} l_j, \sum_{j=1}^{n} m_j, \sum_{j=1}^{n} u_j\right), \tag{7}$$

and to obtain $\left[\sum_{i=1}^{n}\sum_{j=1}^{n} M_{C_i}^j\right]^{-1}$, the fuzzy addition operation of $M_{C_i}^j (j = 1, 2, \dots, n)$ values is performed, such as:

$$\sum_{i=1}^{n}\sum_{j=1}^{n} M_{C_i}^j = \left(\sum_{i=1}^{n} l_i, \sum_{i=1}^{n} m_i, \sum_{i=1}^{n} u_i\right). \tag{8}$$

Then, the inverse of the vector above is computed, such as:

$$\left[\sum_{i=1}^{n}\sum_{j=1}^{n} M_{C_i}^j\right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} u_i}, \frac{1}{\sum_{i=1}^{n} m_i}, \frac{1}{\sum_{i=1}^{n} l_i}\right). \tag{9}$$

From Table 6, according to extent analysis, synthesis values with respect to project manager technical competency are calculated as in Eq. (6):

$$\begin{aligned}
S_{C1} &= (23.1, 35.5, 51.3) \otimes (810.9, 576.5, 379.3)^{-1} \\
&= (0.02, 0.06, 0.13), \\
S_{C2} &= (26.4, 44.7, 64) \otimes (810.9, 576.5, 379.3)^{-1} \\
&= (0.03, 0.07, 0.16), \\
S_{C3} &= (15.5, 26.5, 41.3) \otimes (810.9, 576.5, 379.3)^{-1} \\
&= (0.01, 0.04, 0.109), \\
S_{C4} &= (16.3, 23.1, 32.7) \otimes (810.9, 576.5, 379.3)^{-1} \\
&= (0.02, 0.04, 0.08), \\
S_{C5} &= (14.1, 14.7, 17.2) \otimes (810.9, 576.5, 379.3)^{-1} \\
&= (0.01, 0.02, 0.04), \\
S_{C6} &= (15.9, 20.4, 26.7) \otimes (810.9, 576.5, 379.3)^{-1} \\
&= (0.02, 0.03, 0.07), \\
S_{C7} &= (20.4, 30.7, 42) \otimes (810.9, 576.5, 379.3)^{-1} \\
&= (0.02, 0.05, 0.11), \\
S_{C8} &= (18.4, 28.7, 40) \otimes (810.9, 576.5, 379.3)^{-1} \\
&= (0.02, 0.05, 0.10), \\
S_{C9} &= (23.2, 37.3, 52) \otimes (810.9, 576.5, 379.3)^{-1} \\
&= (0.02, 0.06, 0.13),
\end{aligned}$$

Table 6: Fuzzy pair-wise comparison for project manager class between technical competencies.

Technical competency	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}	C_{17}	C_{18}	C_{19}	C_{20}
C_1	N	M^{-1}	W^{-1}	W^{-1}	S	N	W^{-1}	N	W^{-1}	N	N	N	N	W	W	W^{-1}	N	S	W	W
C_2	M	N	M	M	W	W	N	W^{-1}	N	W	N	N	W^{-1}	W	W	N	N	M	N	N
C_3	W	M^{-1}	N	W	M	N	N	W^{-1}	N	W^{-1}	W^{-1}	N	W^{-1}	W^{-1}	W	W	N	N	W^{-1}	W^{-1}
C_4	W	M^{-1}	W^{-1}	N	W	N	N	W^{-1}	N	N	W^{-1}	N	W^{-1}	W^{-1}	M^{-1}	M	N	N	N	N
C_5	S^{-1}	W^{-1}	M^{-1}	W^{-1}	N	N	N	N	N	N	N	N	N	M^{-1}	N	M^{-1}	W^{-1}	N	N	N
C_6	N	W^{-1}	N	N	N	N	M^{-1}	N	M^{-1}	N	N	W	N	W	N	N	N	N	W^{-1}	W^{-1}
C_7	W	N	N	N	N	M	N	W	N	N	N	W^{-1}	N	W	N	N	N	W	W^{-1}	N
C_8	N	N	W	W	W	N	W^{-1}	N	W^{-1}	N	N	N	N	W	W	N	N	N	N	N
C_9	W	N	N	N	N	M	N	W	N	W^{-1}	N	N	W	N	W	W	N	W	N	N
C_{10}	N	W^{-1}	W	N	N	N	N	N	W	N	W^{-1}	N	M^{-1}	W	M	W	M^{-1}	N	W	S
C_{11}	N	N	W	W	N	N	N	N	N	W	N	W	M	N	W^{-1}	W	N	N	W^{-1}	N
C_{12}	N	N	N	N	N	W^{-1}	W	N	N	N	W^{-1}	N	W	N	W	N	N	N	N	N
C_{13}	N	W	W	W	N	N	N	N	W^{-1}	M	M^{-1}	W^{-1}	N	W	W^{-1}	W	N	N	N	N
C_{14}	W^{-1}	W^{-1}	W	W	M	W^{-1}	W^{-1}	W^{-1}	N	W^{-1}	N	N	W^{-1}	N	W^{-1}	W	N	N	W	W
C_{15}	W^{-1}	W^{-1}	W^{-1}	M	N	N	N	W^{-1}	W^{-1}	M^{-1}	W	W^{-1}	W	W	N	M	W^{-1}	N	N	N
C_{16}	W	N	W^{-1}	M^{-1}	M	N	N	N	W^{-1}	W^{-1}	W^{-1}	N	W^{-1}	W^{-1}	M^{-1}	N	M^{-1}	M^{-1}	N	N
C_{17}	N	N	N	N	W	N	N	N	N	W	N	N	N	N	W	M	N	W	W	W
C_{18}	S^{-1}	M^{-1}	N	N	N	N	W^{-1}	N	M^{-1}	W^{-1}	N	N	N	N	N	M	M^{-1}	N	M^{-1}	W
C_{19}	W^{-1}	N	W	N	N	W	W	N	N	M^{-1}	W	N	N	W^{-1}	N	N	W^{-1}	W	N	N
C_{20}	W^{-1}	N	W	N	N	W	N	N	N	S^{-1}	N	N	N	W^{-1}	N	N	W^{-1}	W^{-1}	N	N

N: Not important; W: Weak important; M: Moderate important; S: Strong important; X: Extreme important.

$$S_{C10} = (24.7, 39.1, 54.7) \otimes (810.9, 576.5, 379.3)^{-1} = (0.03, 0.06, 0.14),$$

$$S_{C11} = (20.4, 32.7, 46) \otimes (810.9, 576.5, 379.3)^{-1} = (0.02, 0.05, 0.12),$$

$$S_{C12} = (18.4, 25.3, 32) \otimes (810.9, 576.5, 379.3)^{-1} = (0.02, 0.04, 0.08),$$

$$S_{C13} = (18.7, 32.1, 45.3) \otimes (810.9, 576.5, 379.3)^{-1} = (0.02, 0.05, 0.12),$$

$$S_{C14} = (15.6, 28.7, 46) \otimes (810.9, 576.5, 379.3)^{-1} = (0.01, 0.05, 0.12),$$

$$S_{C15} = (17.5, 28.5, 43.3) \otimes (810.9, 576.5, 379.3)^{-1} = (0.02, 0.04, 0.11),$$

$$S_{C16} = (13.8, 18.8, 27.3) \otimes (810.9, 576.5, 379.3)^{-1} = (0.01, 0.03, 0.07),$$

$$S_{C17} = (26, 40, 54) \otimes (810.9, 576.5, 379.3)^{-1} = (0.03, 0.06, 0.14),$$

$$S_{C18} = (16.1, 26.6, 26.5) \otimes (810.9, 576.5, 379.3)^{-1} = (0.02, 0.03, 0.07),$$

$$S_{C19} = (18.7, 29.2, 41.3) \otimes (810.9, 576.5, 379.3)^{-1} = (0.02, 0.05, 0.10),$$

$$S_{C20} = (15.9, 20.5, 27.2) \otimes (810.9, 576.5, 379.3)^{-1} = (0.02, 0.03, 0.07).$$

7.4. Compare fuzzy values

As $M_1 = (l_1, m_1, u_1)$ and $M_2 = (l_2, m_2, u_2)$ are two triangular fuzzy numbers, and x_1 and x_2 exist such that $x_2 \geq x_1$, the degree of possibility of $M_1 = (l_1, m_1, u_1) \leq M_2 = (l_2, m_2, u_2)$ is defined as:

$$V(M_2 \geq M_1) = \sup_{x_2 \geq x_1} \lfloor \min(\mu_{M_1}(x_1), \mu_{M_2}(x_2)) \rfloor, \quad (10)$$

where sup represents supremum (i.e. the last upper bound of a set). The degree of possibility for two convex fuzzy numbers can be obtained by using Eq. (11).

$$V(M_2 \geq M_1) = \mathrm{hgt}(M_1 \cap M_2) = d = \begin{cases} 1, & \text{if } m_2 \geq m_1 \\ 0, & \text{if } l_1 \geq u_2 \\ \dfrac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)}, & \text{otherwise} \end{cases} \quad (11)$$

where hgt represents the highest, and d is the ordinate of the highest intersection point between μ_{M_1} and μ_{M_2} as shown in Figure 3, which illustrates Eq. (11).

From Table 6, these fuzzy values are compared by using Eq. (11), and these values are obtained:

$V(S_{C1} \geq S_{C2}) = 0.87, \quad V(S_{C1} \geq S_{C3}) = 1,$
$V(S_{C1} \geq S_{C3}) = 1, \quad V(S_{C1} \geq S_{C5}) = 1,$
$V(S_{C1} \geq S_{C6}) = 1, \quad V(S_{C1} \geq S_{C7}) = 1,$
$V(S_{C1} \geq S_{C8}) = 1, \quad V(S_{C1} \geq S_{C8}) = 1,$
$V(S_{C1} \geq S_{C9}) = 0.97, \quad V(S_{C1} \geq S_{C10}) = 0.95,$
$V(S_{C1} \geq S_{C11}) = 1, \quad V(S_{C1} \geq S_{C12}) = 1,$
$V(S_{C1} \geq S_{C13}) = 1, \quad V(S_{C1} \geq S_{C14}) = 1,$
$V(S_{C1} \geq S_{C14}) = 1, \quad V(S_{C1} \geq S_{C16}) = 1,$
$V(S_{C1} \geq S_{C17}) = 0.9, \quad V(S_{C1} \geq S_{C18}) = 1,$
$V(S_{C1} \geq S_{C19}) = 1, \quad V(S_{C1} \geq S_{C20}) = 1.$

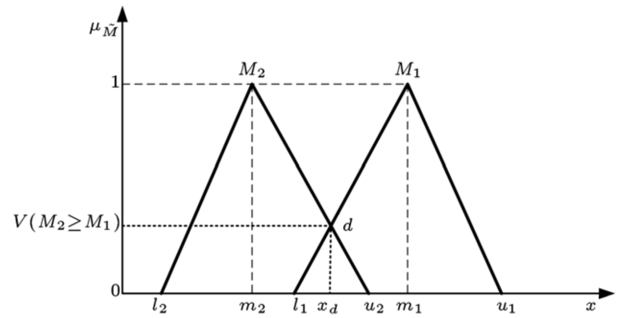

Figure 3: The comparison of two fuzzy numbers, M_1 and M_2.

In a similar way, other fuzzy values of project manager technical competency, respectively, from Table 6, are compared to continue this step.

7.5. Calculate priority weights

The degree of possibility for a convex fuzzy number, M, to be greater than the number of k convex fuzzy numbers, $M_i(i = 1, 2, \ldots, k)$, can be defined by:

$$\begin{aligned} V(M \geq M_1, M_2, \ldots, M_k) &= V[(M \geq M_1), (M \geq M_2), \ldots, (M \geq M_k)] \\ &= \min V(M \geq M_1), \qquad i = 1, 2, \ldots, k. \end{aligned} \quad (12)$$

Assume that $d'(C_1) = \min V(S_i \geq S_k)$ for $k = 1, 2, \ldots, n$; $k \neq i$, and n is the number of competency criteria, as previously described. Then a weight vector is given by:

$$W' = (d'(C_1), d'(C_2), \ldots, d'(C_n)), \quad (13)$$

where $C_i(i = 1, 2, \ldots, n)$ are the nth competency criteria.

As shown in Table 7, priority weights are calculated by using Eq. (12) from data of Table 6.

7.6. Normalize weight vectors

Hence each $d'(C_i)$ value represents the relative preference of each competency criteria. To allow the values in the vector to be analogous to weights defined by AHP type methods, vector W' is normalized and denoted by:

$$W = (d(C_1), d(C_2), \ldots, d(C_n)), \quad (14)$$

where vector W is a non-fuzzy number.

From Table 7, the normalized priority weight vectors are calculated using Eq. (14):

$$\begin{aligned} W = (&0.871, 1, 0.708, 0.588, 0.498, 0.473, 0.763, \\ &0.724, 0.892, 0.920, 0.810, 0.607, 0.788, 0.762, \\ &0.745, 0.468, 0.931, 0.473, 0.740, 0.483). \end{aligned}$$

7.7. Determine the importance of the competency indicators

In the process of accomplishing an employee selection strategy, priority weight vectors are assigned to competency indicators, based on the center area of competency indicators. These priorities will be determined linguistically by selecting values of variable Y. The linguistic importance set of competency indicators is: $Y = \{y_1, y_2, y_3, y_4, y_5\}$= {Not important; Less important; Important; More important; Extreme important}.

Table 7: Priority weights of project manager technical competencies.

Degree of possibility	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}	C_{17}	C_{18}	C_{19}	C_{20}
$d'(C_1)$	1	0.87	1	1	1	1	1	1	0.97	0.95	1	1	1	1	1	1	0.93	1	1	1
$d'(C_2)$	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
$d'(C_3)$	0.83	0.70	1	1	1	1	0.92	1	0.81	0.78	0.88	1	0.91	0.96	0.96	1	0.76	1	0.94	1
$d'(C_4)$	0.72	0.58	0.91	1	1	1	0.82	0.86	0.69	0.66	0.78	0.94	0.81	0.87	0.87	1	0.64	1	0.85	1
$d'(C_5)$	0.51	0.49	0.56	0.63	1	0.72	0.52	0.58	0.59	0.66	0.59	0.55	0.63	0.51	0.69	0.80	0.63	0.71	0.67	0.72
$d'(C_6)$	0.60	0.47	0.82	0.91	1	1	0.71	0.76	0.58	0.55	0.68	0.84	0.71	0.78	0.77	1	0.52	0.99	0.75	0.99
$d'(C_7)$	0.90	0.76	1	1	1	1	1	1	0.87	0.84	0.96	1	0.99	1	1	1	0.82	1	1	1
$d'(C_8)$	0.86	0.72	1	1	1	1	0.95	1	0.83	0.80	0.92	1	0.94	1	1	1	0.78	1	0.98	1
$d'(C_9)$	1	0.89	1	1	1	1	1	1	1	0.97	1	1	1	1	1	1	0.95	1	1	1
$d'(C_{10})$	1	0.92	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.98	1	1	1
$d'(C_{11})$	0.94	0.81	1	1	1	1	1	1	0.92	0.89	1	1	1	1	1	1	0.87	1	1	1
$d'(C_{12})$	0.75	0.60	0.96	1	1	1	0.86	0.91	0.72	0.69	0.82	1	0.85	0.91	0.91	1	0.67	1	0.90	1
$d'(C_{13})$	0.91	0.78	1	1	1	1	1	1	0.89	0.86	0.97	1	1	1	1	1	0.85	1	1	1
$d'(C_{14})$	0.88	0.76	1	1	1	1	0.96	1	0.86	0.83	0.93	1	0.95	1	1	0.81	1	0.99	1	0.88
$d'(C_{15})$	0.87	0.74	1	1	1	1	0.96	0.99	0.84	0.82	0.92	1	0.95	0.99	1	1	0.80	1	0.98	1
$d'(C_{16})$	0.59	0.46	0.79	0.87	1	0.95	0.69	0.74	0.57	0.54	0.66	0.81	0.69	0.75	0.74	1	0.52	0.94	0.73	0.94
$d'(C_{17})$	1	0.93	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
$d'(C_{18})$	0.61	0.47	0.83	0.92	1	1	0.72	0.77	0.58	0.55	0.68	0.85	0.71	0.78	0.77	1	0.53	1	0.75	1
$d'(C_{19})$	0.87	0.74	1	1	1	1	0.97	1	0.85	0.82	0.93	1	0.96	1	1	1	0.80	1	1	1
$d'(C_{20})$	0.61	0.48	0.83	0.92	1	1	0.72	0.77	0.59	0.56	0.68	0.85	0.72	0.78	0.78	1	0.53	0.99	0.76	1

Table 8: Numerical values for importance of the competency indicators.

Linguistic variable	Fuzzy number	Center value	Priorities weight interval
Not important	[1, 0.9, 0.8, 0.7, 0.6, 0.5, 0.4, 0.3, 0.2, 0.1, 0]	0.333	$0 \leq W \leq 0.375$
Less important	[1, 0.99, 0.96, 0.91, 0.84, 0.75, 0.64, 0.51, 0.36, 0.19, 0]	0.375	$0.375 \leq W \leq 0.666$
Important	[0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1]	0.666	$0.666 \leq W \leq 0.750$
More important	[0, 0.01, 0.04, 0.09, 0.16, 0.25, 0.36, 0.49, 0.64, 0.81, 1]	0.750	$0.750 \leq W \leq 0.933$
Extreme important	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0.5, 1]	0.933	$0.933 \leq W \leq 1$

Table 9: Linguistic evaluation of importance of the competency indicators for each class.

Class	Competency	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}	C_{17}	C_{18}	C_{19}	C_{20}
Project manager	Technical	M	E	I	L	L	L	M	I	M	M	M	L	M	M	I	L	M	L	I	L
	Behavioral	E	E	M	I	I	L	M	M	I	M	M	M	I	I	I					
	Contextual	E	M	M	M	I	I	I	M	M	I	I									
Engineer	Technical	E	M	E	M	I	I	L	M	I	M	I	I								
	Behavioral	E	M	I	I	M	L	I	L	N	L	I	M	I	M						
	Contextual	M	I	L	N	M	E	I	M	M	I	I									
Technician	Technical	E	I	I	M	I	I	I	I	M											
	Behavioral	M	I	I	E	M	I	I	L	I	L	I									
	Contextual	E	M	M	I	I	L	M	I	I	L										
Laborer	Technical	M	M	I	I	L	I	I	L	N											
	Behavioral	E	I	M	M	M	I	E	I	N	M										
	Contextual	E	E	M	M	I	I	I	L	I	I	I	L	I							

N: Not important; L: Less important; I: Important; M: More important; E: Extreme important.

The membership function of each fuzzy linguistic variable for the importance of competency indicators is presented in Figure 4, and Table 8 explains the numerical values of membership functions.

The priorities weight interval is shown in Table 8. Utilizing the methodology proposed in this study, each competency in the project manager, engineer, technician and laborer classes is rated using the membership functions in Figure 4, as shown in Table 9.

7.8. Measure of employee competency

The linguistic evaluation set for each measure indicator for an employee is:

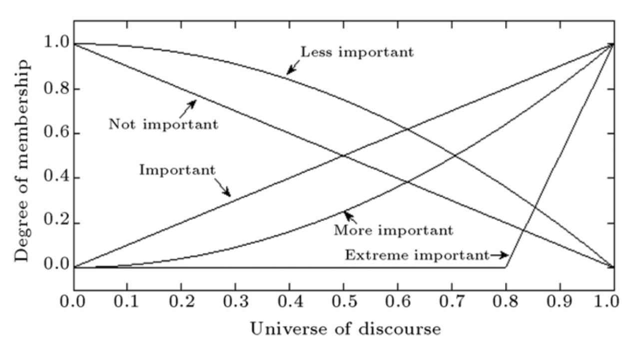

Figure 4: Membership functions for importance of competency indicators.

Table 10: Linguistic evaluation of the competency of an employee for factor indicators.

Employee indicator	Project manager employee selection					
	Technical competency	Employee	Behavioral competency	Employee	Contextual competency	Employee
C_1	Project management success	G	Leadership	S	Project orientation	A
C_2	Interested parties	S	Engagement & motivation	S	Programme orientation	A
C_3	Project requirements	G	Self-control	P	Portfolio orientation	F
C_4	Risk & opportunity	A	Assertiveness	A	PPP implementation	A
C_5	Quality	G	Relaxation	A	Permanent organization	F
C_6	Project organization	S	Openness	G	Business	F
C_7	Teamwork	A	Creativity	F	Systems, products & technology	G
C_8	Problem resolution	G	Results orientation	A	Personnel management	A
C_9	Project structures	G	Efficiency	G	Health, safety & environment	P
C_{10}	Scope & deliverables	S	Consultation	P	Finance	A
C_{11}	Time & project phases	S	Negotiation	G	Legal	F
C_{12}	Resources	G	Conflict & crisis	F		
C_{13}	Cost & finance	G	Reliability	P		
C_{14}	Procurement & contract	S	Values appreciation	G		
C_{15}	Changes	G	Ethics	A		
C_{16}	Control & reports	S				
C_{17}	Information & documentation	G				
C_{18}	Communication	A				
C_{19}	Start-up	G				
C_{20}	Close-out	G				

P: Poor; F: Fair; A: Average; G: Good; S: Superior.

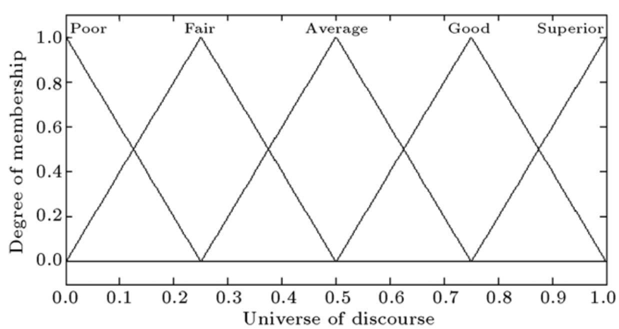

Figure 5: Membership functions for employee competency.

$$X = \{x_1, x_2, x_3, x_4, x_5\}$$
$$= \{\text{Poor, Fair, Average, Good, Superior}\}.$$

The membership function of each fuzzy linguistic variable for the evaluation is presented in Figure 5. By interview of the operations manager or the human expert by employees, or even self-assessment, a linguistic competency evaluation of each employee for each competency factor is performed. For example, a project manager's competency, which is evaluated by an interviewer, is given in Table 10.

7.9. Determine the employees evaluated

The set of employees that are evaluated by each class of personnel is defined as:

$$E = \{e_j\}, \quad j = 1, 2, \ldots, J,$$
$J =$ the number of employees.

7.10. Calculating the fuzzy value of the main competency factor

In the methodology described in this study, the linguistic competency evaluations of x_{C_i} are appointed by the interviewer for the C_i, ith competency indicator and the linguistic importance of the competency indicators of y_{C_i} for the C_i, ith competency indicator are measured in this study (as shown in Table 9).

For employee e_j, the evaluation of the main competency factor is a fuzzy relation equation, which is calculated using a multiply operator (Eq. (2)). The membership function values of the fuzzy relation of sub-competency factors are expressed as:

$$z_{C_i} = x_{C_i}.y_{C_i}, \tag{15}$$

$$Z = \frac{\sum_{C_i} z_{C_i}}{\sum_{C_i} y_{C_i}}, \tag{16}$$

where z_{C_i} are the membership function values of the fuzzy relation of the ith sub-competency factor, and Z is consist of the membership function values of the fuzzy relation of the main competency factors that are technical, behavioral or contextual.

For example, from Table 10, we see that for project management success indicator C_1, the employee competency indicator is assessed as 'Good' for the employee in his/her competency evaluation by the interviewer. The importance of the competency indicator, C_1, has been measured to be a more important indicator in this study, as shown in Table 9. This relationship between indicator importance and assessment is expressed by the fuzzy relation, f_1, which is illustrated below (see Eqs. (2) and (15)):

$$z_1 = [0, 0, 0, 0, 0, 0, 0.4, 0.8, 0.8, 0.4, 0]$$
$$\times [0, 0.01, 0.04, 0.09, 0.16, 0.25, 0.36, 0.49, 0.64, 0.81, 1]$$
$$= [0, 0, 0, 0, 0, 0, 0.144, 0.392, 0.512, 0.324, 0],$$

for $x_{C_1} =$ Good and $y_{C_1} =$ More important.

In a similar way, fuzzy relations representing 20 competency entries for project manager technical competency factors, respectively, in Table 11, are calculated.

To complete this step, from Eq. (16), membership function values of the fuzzy value for the technical competency of the project manager, which is the input of the next stage, are determined as:

$$Z = [0.00, 0.00, 0.00, 0.05, 0.13, 0.19, 0.34,$$
$$0.52, 0.55, 0.42, 0.31].$$

Table 11: Fuzzy relation values for project manager technical competency.

Fuzzy relation	Universe of discourse										
	0.00	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	1.00
z_{C1}	0.00	0.00	0.00	0.00	0.00	0.00	0.14	0.39	0.51	0.32	0.00
z_{C2}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.30	1.00
z_{C3}	0.00	0.00	0.00	0.00	0.00	0.00	0.24	0.56	0.64	0.36	0.00
z_{C4}	0.00	0.00	0.00	0.18	0.50	0.75	0.38	0.10	0.00	0.00	0.00
z_{C5}	0.00	0.00	0.00	0.00	0.00	0.00	0.26	0.41	0.29	0.08	0.00
z_{C6}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.11	0.00
z_{C7}	0.00	0.00	0.00	0.02	0.10	0.25	0.22	0.10	0.00	0.00	0.00
z_{C8}	0.00	0.00	0.00	0.00	0.00	0.00	0.24	0.56	0.64	0.36	0.00
z_{C9}	0.00	0.00	0.00	0.00	0.00	0.00	0.14	0.39	0.51	0.32	0.00
z_{C10}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.13	0.49	1.00
z_{C11}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.13	0.49	1.00
z_{C12}	0.00	0.00	0.00	0.00	0.00	0.00	0.26	0.41	0.29	0.08	0.00
z_{C13}	0.00	0.00	0.00	0.00	0.00	0.00	0.14	0.39	0.51	0.32	0.00
z_{C14}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.13	0.49	1.00
z_{C15}	0.00	0.00	0.00	0.00	0.00	0.00	0.24	0.56	0.64	0.36	0.00
z_{C16}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.11	0.00
z_{C17}	0.00	0.00	0.00	0.00	0.00	0.00	0.14	0.39	0.51	0.32	0.00
z_{C18}	0.00	0.00	0.00	0.18	0.50	0.75	0.38	0.10	0.00	0.00	0.00
z_{C19}	0.00	0.00	0.00	0.00	0.00	0.00	0.24	0.56	0.64	0.36	0.00
z_{C20}	0.00	0.00	0.00	0.00	0.00	0.00	0.26	0.41	0.29	0.08	0.00

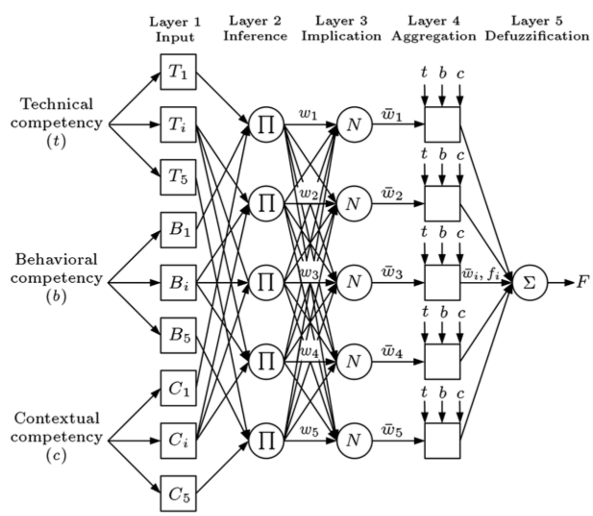

Figure 6: Proposed ANFIS model architecture.

8. Developing ANFIS

A fuzzy inference system is a knowledge-based system that contains the fuzzy algorithm in a rule base. In this system, knowledge, encoded in the rule base, is originated from human experience and historical data, and the rules represent relationships between inputs and outputs of a system [47]. The ANFIS is a fuzzy model that puts data in the framework of adaptive systems to facilitate learning and adaptation [48]. Such a framework makes the ANFIS modeling more systematic and less reliant on expert knowledge [48]. Applied ANFIS architecture [49] consists of five layers, as shown in Figure 6.

To present the ANFIS architecture, five fuzzy 'IF-THEN' rules are considered:

Rule 1: If t is T_1 and b is B_1 and c is C_1,
then, $f_1 = p_1.t + q_1.b + r_1.c + s$;

$\vdots$

Rule i: If t is T_i and b is B_i and c is C_i,
then, $f_i = p_i.t + q_i.b + r_i.c + s$;

$\vdots$

Rule 5: If t is T_5 and b is B_5 and c is C_5,
then, $f_5 = p_5.t + q_5.b + r_5.c + s$;

The output of each layer, O_i, and parameters of the developed ANFIS are described as follows:

Layer 1: *Input layer.* Inputs of the system are technical, behavioral and contextual competency, denoted, respectively, as t, b and c, which were calculated in the previous fuzzy AHP stage as the fuzzy value of each person's main competency, denoted as Z. We choose μ_{T_i}, μ_{B_i} and μ_{C_i} to be triangular-shaped membership functions with a maximum equal to 1 and a minimum equal to 0, as defined in Section 7.1, where $\{l_i, m_i, u_i\}$ is the premise parameter set that will adjust with the learning algorithm. To map fuzzy input variables into each member function, i, of employee competency fuzzy sets, the product operator is used:

$$O_1^1 = \mu_{T_i}(t) = t.\mu_{T_i}, \quad i = 1, 2, 3, 4, 5, \tag{17a}$$

$$O_2^1 = \mu_{B_i}(b) = b.\mu_{B_i}, \quad i = 1, 2, 3, 4, 5, \tag{17b}$$

$$O_3^1 = \mu_{C_i}(c) = c.\mu_{C_i}, \quad i = 1, 2, 3, 4, 5. \tag{17c}$$

Layer 2: *Inference layer or rule layer.* Firing strength, w_i, which shows the degree of satisfaction of the premise part of the fuzzy rule, is generated with a T-norm operator that performs the fuzzy conjunction "AND" for each member function, I;

$$O_i^2 = w_i = \mu_{T_i}(t) \cdot \mu_{B_i}(b) \cdot \mu_{C_i}(c), \quad i = 1, 2, 3, 4, 5. \tag{18}$$

Layer 3: *Implication layer.* The main purpose of this layer is to calculate the ratio of the ith rule's firing strength to the sum of all firing strength:

$$O_i^3 = \overline{w}_i = \frac{w_i}{\sum w_i}, \quad i = 1, 2, 3, 4, 5, \tag{19}$$

where outputs, $\overline{w}_i$, are referred to as normalized firing strengths and the value is between 0 and 1.

Layer 4: *Aggregation layer*. In this layer, the normalized firing strengths are multiplied with the function of the Sugeno fuzzy rule;

$$O_i^4 = \overline{w}_i.f_i = \overline{w}_i.(p_i.t + q_i.b + r_i.c + s_i), \quad i = 1, 2, 3, 4, 5, \tag{20}$$

where $\{p_i, q_i, r_i, s_i\}$ is the consequent parameter set that will adjust with the learning algorithm.

Layer 5: *DeFuzzification layer*. The weighted averaged method is used to perform the process of defuzzification, which transforms the fuzzy result into a crisp output, F [49].

$$O_i^5 = F = \sum \overline{w}_i, f_i, \quad i = 1, 2, 3, 4, 5. \tag{21}$$

The particulars of each step for an ANFIS applied to the personnel selection problem are outlined below.

8.1. Identification of input and output variables

The first step in preparing fuzzy rules is to collect historical data. Data regarding fuzzy system input and output should be collected. In the current study, data were gathered through 40 previously conducted interviews by expert managers of different Iranian construction companies, who were selecting some project managers, engineers, technicians and laborers, to the extent of 10 interviews per each personnel class. This data contain each interviewee's features and competency ranking.

All interviews were conducted by chief officers of the companies, as they were considered the most qualified for making hiring decisions. The linguistic competency evaluations earned by each candidate for each criterion were left to these experts. Then each candidate received a fuzzy value on the basis of calculation of the previous fuzzy AHP stage for each main competency. It should be mentioned that these evaluations do not require a high level of accuracy; the ability to work with such ambiguity and lack of precision are features of fuzzy systems.

In this study, based on collected data, the ANFIS outputs and inputs are clarified. Inputs are derived from the fuzzy AHP algorithm proposed in the previous section for each main competency criterion (technical, behavioral and contextual competency). The output is an employee total score evaluated by the interviewer on the basis of the traditional sum of each competency score multiplied by NII and calculated in the competency development presented in Section 6. Obviously, in cases where the output rate of the first person is greater than that of the second, the first person is better than the second, and vice versa. From a total of 40 interviews, the number of records in the input–output data are 400; 240 records are used to prepare and train the system and 160 are used for analysis and testing.

8.2. Structure identification

The fuzzy system structure is determined by resolving rules and appropriate membership functions for inputs and outputs. Therefore, structure identification is divided into two different steps: (1) membership function identification for inputs and outputs and (2) rule creation. As the goal of the current study is to create a fuzzy system that assists in selecting the personnel of construction projects, according to competency criteria, for system structure identification, the membership functions of outputs are identified using clustering. Then, membership functions of inputs are identified using output data mapping to input data, and the rules are also determined for each membership function as follows.

8.3. Fuzzy output clustering

To create rules, the inputs and outputs should be clustered [50,51]. Clustering analysis comprises a portion of multivariate analysis, and it is also combined with data-mining. It is a technique for classifying data. The basic concept behind clustering is to divide the dataset in such a way that two cases from the same cluster are as similar as possible, while they are as dissimilar as possible from two other cases from different clusters.

To fulfill this purpose, the method of Sugeno and Yasukawa [37] is used. According to this method, at first only the output space is clustered. Afterwards, the input clusters are determined, with a projection of each output cluster to each input space. To cluster the outputs, the fuzzy c-mean clustering method is used [52]. The main shortcomings in this algorithm, in addition to those of the procedure used, are discussed as follows.

The appropriate number of clusters is not specified at first; therefore, a criterion for assessing the suitability of a number of clusters is needed. Many criteria have been identified for this purpose [52]. The criterion selected for the current study is that proposed by Sugeno and Fukuyama; with this criterion, both the compactness and separation between clusters have been considered. The small size of this criterion suggests its suitability [52].

$$S(c) = \sum_{k=1}^{n}\sum_{i=1}^{c}(\mu_{ik})^m \left(\|x_k - v_i\|^2 - \|v_i - \overline{v}\|^2\right), \tag{22}$$

where μ_{ik} is the degree of membership of data number, k, in cluster number, i, n is the number of data, c is the number of clusters, and x_k is the kth data. The two remaining parameters are identified by the following equations [52]:

$$d_{ik} = \|x_k - v_i\|, \tag{23}$$

$$\mu_{ik} = \left(\sum_{j=1}^{c}\left(\frac{d_{ik}}{d_{jk}}\right)^{\frac{2}{m-1}}\right)^{-1}, \quad 1 \le i \le c,\ 1 \le k \le n. \tag{24}$$

Eq. (24) specifies the membership degree of kth data in the ith cluster.

$$v_i = \frac{\sum_{k=1}^{n}(\mu_{ik})^m x_k}{\sum_{k=1}^{n}(\mu_{ik})^m}, \quad 1 \le i \le c. \tag{25}$$

Eq. (25) shows the center of the ith cluster. By using the fuzzy c-mean clustering algorithm and the procedures discussed, to solve the problem with this algorithm, output data were clustered. For the project manager class, as an example of computation procedures, the number of clusters are five for each personnel class, m is equal to 3.4, and the $S(c)$ obtained is 1.3053. The clustering of project manager class outputs is presented in Figure 7.

8.4. Membership function and rule generation

After clustering output data for each of the aforementioned membership functions, the membership function with the shortest distance within the cluster is chosen for that cluster. The declared distance is determined as follows. First, for each available point at the limit within which the cluster is defined, the membership degree based on the defined membership function and created clusters is determined. Then

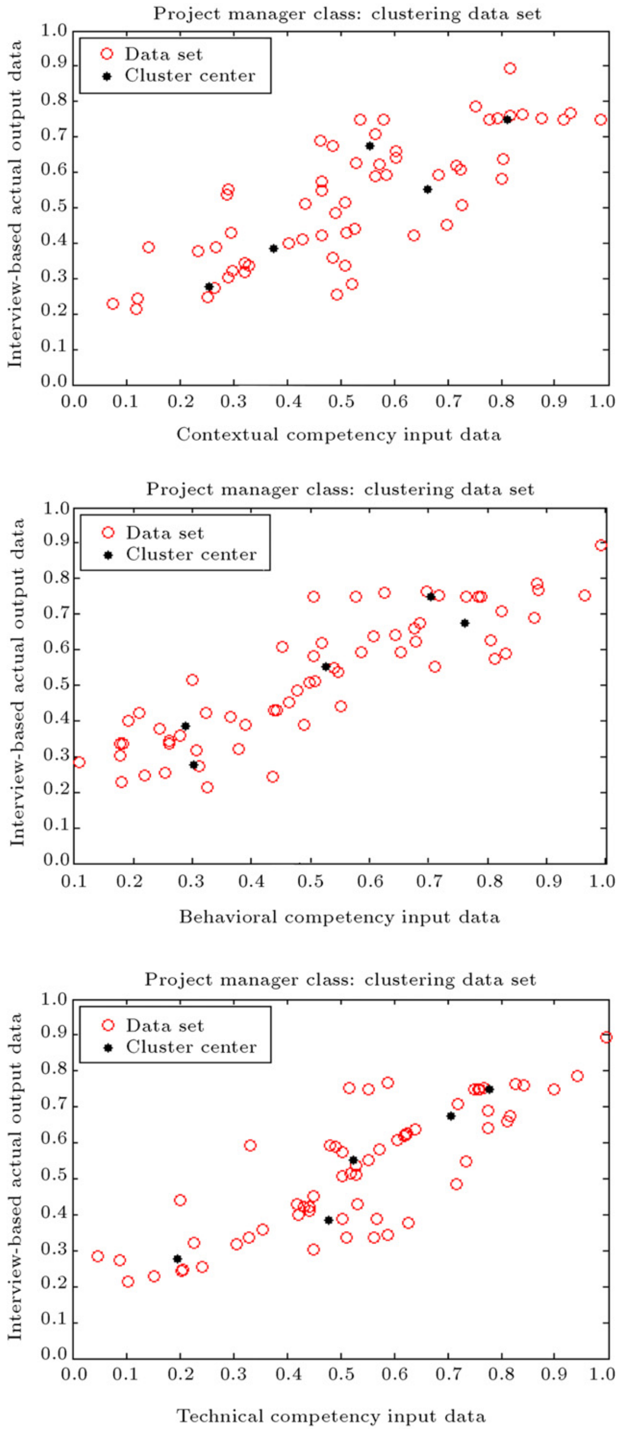

Figure 7: Clustering of project manager class output data.

the absolute difference between these values is determined for each point. The sum of the absolute differences is equal to the declared distance. Then the appropriate membership function is determined for each cluster using MATLAB.

Subsequently, the appropriate membership functions created on each output are projected on input membership functions, and the fuzzy rules are determined. Input membership functions have been defined to be triangular for technical, behavioral and contextual competency. In this system, 5 fuzzy rules have been produced for each personnel class.

8.5. Parameter identification

The parameters related to membership functions that were specified inaccurately, according to clustering, need to be tuned. The objective in tuning parameters related to the membership function is to decrease system error as much as possible.

It can be observed that there are two adaptive layers in this ANFIS architecture, namely, the first and fourth layers. In the first layer, there are modifiable parameters, $\{l_i, m_i, u_i\}$, which are related to the input membership functions. These parameters are the so-called premise parameters. In the proposed system, the available data, and consequently the numbers produced by comparing available data are very limited. Hence, the Triangular Fuzzy Number (TFN) is the most appropriate for such criteria. For each system input, five TFNs are defined. In the fourth layer, there are modifiable parameters, $\{p_i, q_i, r_i, s_i\}$, pertaining to the first order polynomial. These parameters are so-called consequent parameters [49]. To determine the best parameters for fuzzy input and output numbers, input–output data are used, and the amount of system error, in relation to output calculations, is determined by a learning algorithm as follows.

8.6. ANFIS learning algorithm

The task of the learning algorithm in this model architecture is to tune modifiable parameters, namely, $\{l_i, m_i, u_i\}$ and $\{p_i, q_i, r_i, s_i\}$, and to make the ANFIS output match the training data. When the premise parameters $\{l_i, m_i, u_i\}$ of input membership functions are fixed, the output of the ANFIS model, substituting Eq. (20) into Eq. (21), can be expressed as:

$$\begin{aligned} F &= \sum \overline{w}_i . f_i \\ &= \sum ((\overline{w}_i . t)p_i + (\overline{w}_i . b)q_i + (\overline{w}_i . c)r_i + (\overline{w}_i)s_i), \end{aligned} \tag{26}$$

which is a linear combination of the modifiable consequent parameters $\{p_i, q_i, r_i, s_i\}$. The Least Squares Estimate (LSE) method can easily be used to identify the optimal values of these parameters. When the premise parameters are not fixed, the search space becomes larger and convergence of the training becomes slower. A hybrid algorithm combining the LSE and gradient descent methods is adopted to solve this problem.

The current study uses a hybrid algorithm to train fuzzy system parameters. The hybrid algorithm is composed of a forward and backward pass. The LSE 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 optimally adjust 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 back-propagation algorithm. It has been proven that this hybrid algorithm is highly efficient in training the ANFIS [49].

An overall error measure for each personnel class is shown in Table 12. This table emphasizes that by using the learning algorithm, reliable results may be gained. Figure 8 shows the performance of the developed model for the training data set, based on a comparison of model output and actual data for each personnel class. As seen in this figure, due to a similarity between model output and actual data, the performance of the model is satisfactory.

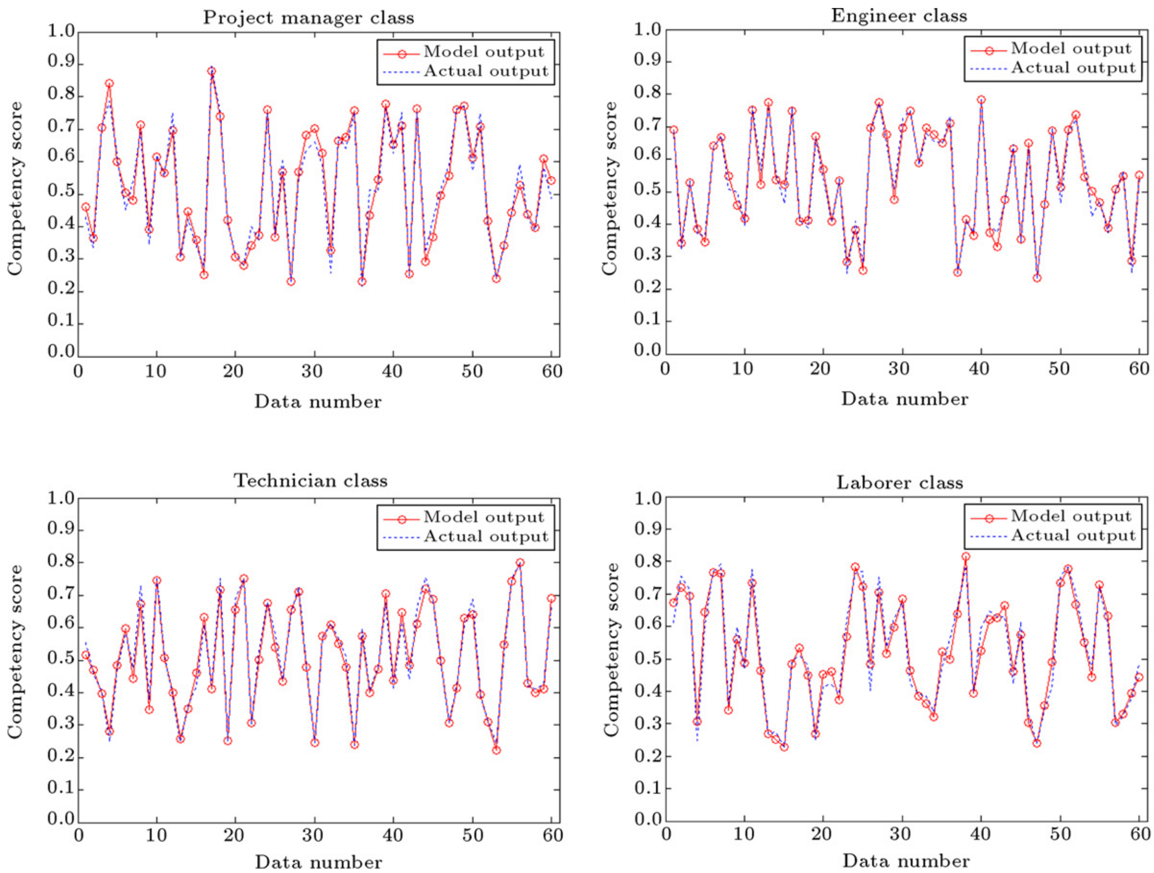

Figure 8: Comparison between model output and actual data for each personnel class.

Table 12: Overall error measure for each personnel class.

ANFIS model	Overall error measure	
	Training	Testing
Project manager class	0.0326	0.0415
Engineer class	0.0234	0.0490
Technician class	0.0222	0.0450
Laborer class	0.0332	0.1258

Table 13: The performance of each class model.

ANFIS model	Root means square error		Correlation factor	
	Training	Testing	Training	Testing
Project manager class	0.0994	0.0935	0.9828	0.9720
Engineer class	0.0875	0.0972	0.9883	0.9720
Technician class	0.0760	0.0939	0.9896	0.9461
Laborer class	0.0850	0.2024	0.9801	0.7697

8.7. Training the model

At this stage, the proposed method is implemented for ranking of personnel, based on their competency scores. Two norms were used for comparative evaluation of the performance of the model. These norms are Root Mean Square Error (RMSE) and Correlation Factor (CF) between model results, f, and actual data, f', according to Eqs. (27) and (28), respectively:

$$\mathrm{RMSE} = \sqrt{\frac{\sum(f_i - f_i')}{n}}, \qquad (27)$$

$$\mathrm{CF} = \frac{\sum(f_i - \bar{f})(f_i' - \bar{f'})}{\sqrt{\sum(f_i - \bar{f})^2 \sum(f_i' - \bar{f'})^2}}, \qquad (28)$$

where n is the total number of data, f_i is the ith model result, f_i' is ith actual data, $\bar{f}$ is the sample mean of the model result and $\bar{f'}$ is the sample mean of actual data.

The proposed fuzzy system has been trained using 240 existing case studies; 60 for each class. The results of modeling are summarized in Table 13. It can be seen in this table that the developed model results are satisfactory in each personnel class. The system undertakes RMSE and CF evaluations properly. Moreover, Figure 8 shows the performance of the developed models for training data. In these figures, the results of the model output are compared with interview-based actual output data. The horizontal axis of these figures is the number of sample data in training records, and the vertical ones are their corresponding competency score. As shown in Figure 8 and approved by findings in Table 13, models have good agreement between their output and expected results.

It is important to compare the performance of the models in training cases. Figure 9 details the comparison results of the fuzzy system and the expected results for each training record. In these figures, the horizontal axis is representative of model results, and the vertical one is related to the results of interview-based actual output training data. The state of being scattered from the diagonal axis is representative of unsuitable results, and the more the points are close to the diagonal axis, the

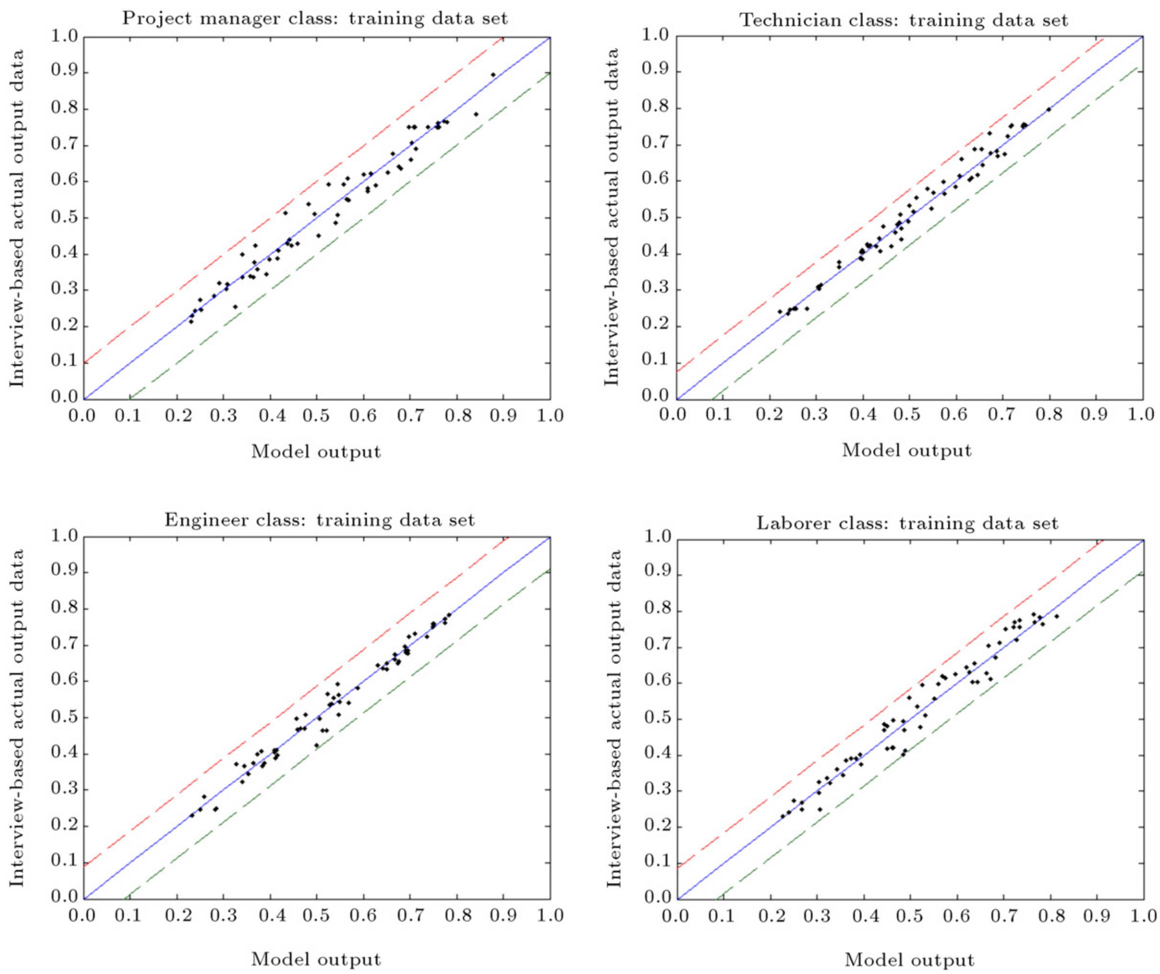

Figure 9: Comparison of model output and actual data by training data set.

better results are gained. Thus developed models can be used as construction personnel selectors.

8.8. Testing the model

The only possible way to measure the validity of a fuzzy expert system is through testing it with a number of actual data and comparing model outputs with actual outputs (results of actual interview-based). The proposed fuzzy system has been analyzed using 160 existing case studies; 40 for each class. As shown in Table 13, the results are satisfactory. The system makes each evaluation properly. In particular, in the case of the testing data set, it can be seen that both RMSE and CF properties of the proposed model are satisfied, which means that models can yield proper predictions for any new and unfamiliar inputs. Figure 10 details comparison results of the fuzzy system and expected results. In these figures, the horizontal axis is representative of model results, and the vertical one is related to the results of interview-based actual output testing data. The state of being scattered from the diagonal axis is representative of unsuitable results, and the more the points be closed to the diagonal axis, the better results are gained. Together with these satisfactory conditions, the system output is very close to expected output. Referring to Table 13 and Figures 8–10, it may be claimed that competency-based construction personnel selection models have satisfactory results.

8.9. Make the final decision to select the employee

The fuzzy values of the employee technical competency scores computed in Section 7.10 and other behavioral and contextual competency are entered into the proposed ANFIS model. The total score obtained, F, is 0.78, 0 of which means poor competent person, and 1 means superior competent person, as shown in Figure 5. Then system stages are operated for the personnel of others and for each class. All personnel are ranked based on their total score. Finally, among each class personnel, we select the most competent employees for satisfying operational performance, since he/she has the highest competency score.

9. Conclusion

In this study, a fuzzy adaptive model for competency-based employee selection and assignment has been delineated and implemented with an example. The presented system can be a convenient alternative to the traditional method of selecting different personnel as a project manager, engineer, technician or laborer. The proposed system was analyzed using existing data. It was found to provide satisfactory results, given that effective and efficient methods were employed to validate employee selection based on competency.

The proposed employee selection framework has the following advantages:

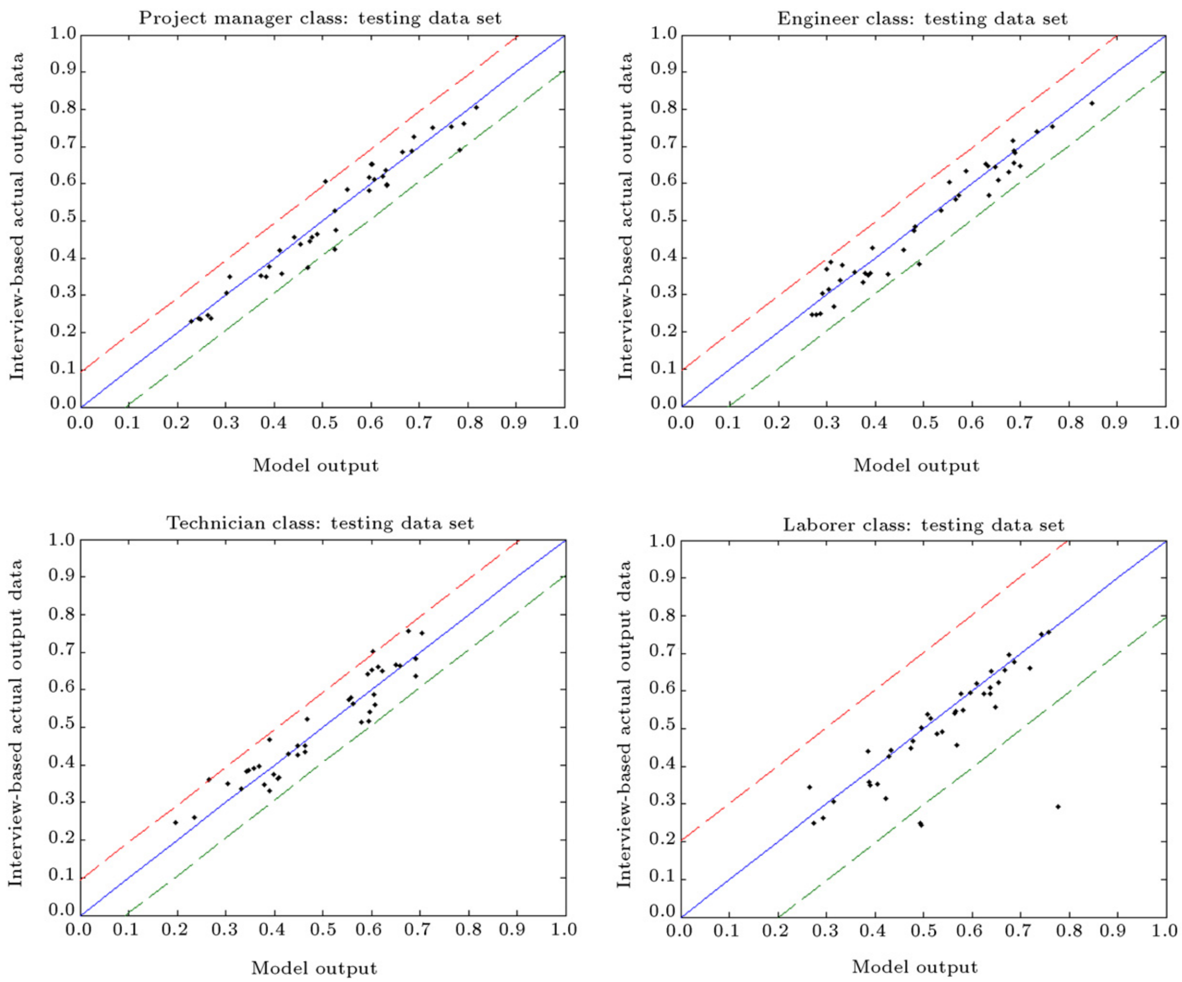

Figure 10: Comparison of model output and actual data by testing data set.

- The hierarchical structure of competency criteria is consistent for different kinds of personnel, project manager, engineer, technician or laborer.
- The system is a precise, useful tool for decision makers of construction companies that lack adequate experience in selecting the best person for project positions, from a number of possible choices.
- Decision-makers can decompose the compound employee selection problem into simple and more logical judgment of the factors.
- The model is flexible enough to integrate extra factors in the evaluation.
- The fuzzy system allows for a two-stage selection process when there are too many candidates for a single position. At the first stage, a limited number of candidates can be prequalified from the entire group of candidates by using the fuzzy system. Then those candidates can be interviewed as usual.
- The model assesses corporate factors and guidance, based on construction project goals. It can not only reduce time and cost during the selection phase, but also diminish conflict and hidden cost at the implementation stage.

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