AN AUTOMATED PROCEDURE FOR SELECTING PROJECT MANAGERS IN CONSTRUCTION FIRMS

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Abstract. Selecting a suitable project manager for construction projects is one of the most important decisions made by construction firms. In the traditional approach, interviews are conducted by senior managers of the company, who consider the project requirements and the candidates' capabilities. However, interviewing candidates is usually time consuming and there is the risk of impaired judgment, leading to human error. Decision-making support systems are therefore very useful. In previous work, the authors proposed a fuzzy system to address the issues described above (Rashidi *et al.* 2011). In this paper, a simpler robust model is presented. The advantages of this new model lie in its simplicity and the fact that it is not necessary to consider many criteria in the selection procedure when using this model. This model only requires 15 fields of candidate information. In the development of this model, the first step is construction of an initial fuzzy model based on all the criteria that may be considered when selecting a project manager. The significance of the coefficients of the criteria are then determined. In the next step, the model is optimized by changing the number of fuzzy rules and reducing the number of criteria. Finally, the most appropriate model is chosen on the basis of the least number of criteria required to obtain accurate results. To show the model's capability, it is used in real interviews. The obtained results indicate the high accuracy of the model in predicting the output, that is, the best candidate in the interviews.

Keywords: construction project manager, fuzzy rules, criteria, input and output data, fuzzy curves.

1. Introduction

In recent years, construction projects have become very complicated technically. The construction project manager usually plays a major role in a project's success. They make most of the important decisions during a project. The selection of a project manager is therefore one of the most significant decisions for construction companies to make. Numerous problems can arise if an unsuitable manager is selected for a construction project.

In the last two decades, many researchers have been exploring the general skills that a project manager should possess, as well as those needed to succeed, and the criteria for the selection of project managers.

Berger (1996) highlighted the growing need for civil engineers with management skills and, perhaps, advanced degrees in engineering management. Perini listed the primary qualities of a successful construction project manager as follows: a high level of technical skill; diligence; and the ability to manage the executive team, communicate effectively, pay attention to the client's demands, prioritize, perform under pressure, ask the right questions, and take responsibility and the necessary risks to achieve goals (Liao 2007). Meredith *et al.* (1995) classified the skills required by a project manager into six distinct groups: communication, organizational, team-building, leadership, coping, and technological. According to Goodwin (1993), conceptual, technical, negotiation, and human resource skills are the four main skills that a project manager should possess. Ogunlana *et al.* (2002) believed that conceptual, human resource, negotiation, and technical skills are the most essential skills for a project manager. Sunindijo *et al.* (2007) studied emotional intelligence (EI) in the context of project manager selection. The results of these studies revealed that EI is beneficial to both the individual and the organization. Pheng and Chuan (2006) identified the factors that effectively influence the performance of a project manager in the private and public sectors. Dolfi and Andrews (2007) studied the personality characteristics of project manager and formulated a conclusive understanding of the motivations of project managers, especially concerning their work environment. A large number of studies have been conducted on the characteristics and responsibilities of project managers; however, only a few of them deal with the selection of project managers. The traditional method for selecting a project manager for a construction firm is to choose the best candidate after interviewing the potential ones. The interview is usually conducted by the construction firm's top managers. This method, however, has two major problems:

1) Interviewing is usually time-consuming, particularly if there are many candidates. There are also time constraints because the construction firm's managers are usually very busy, and they are likely to have limited time. In some cases, it is impossible to interview all the candidates, and, as a result, some suitably qualified candidates may be overlooked;

2) Decision making by humans is usually fraught with error and personal judgment. Additionally, it is possible that the decision maker (interviewer) does not have enough experience to select the most suitable individual and his/her decision making may not be accurate.

Over the past two decades, much research has been carried out on various applications of fuzzy logic for decision making in the construction area.

We have proposed a fuzzy system for solving the problem of selecting project managers in construction companies (Rashidi *et al.* 2011). The selection process in this system requires a large number of criteria (23 criteria). Usually, it is difficult to consider and investigate so many criteria in the selection process. On the other hand, not considering some of the criteria may reduce the accuracy of the selection process.

In this article, two factors – the reduced number of required criteria in project manager selection and the acceptable range of accuracy in predicting results – are considered, and an optimized fuzzy system for the selection process in construction firms is presented. Toward this end, first, all possible criteria for the selection of a project manager were identified and an initial fuzzy expert system was developed on the basis of these criteria. The dataset required to develop and test the system was obtained from a number of interviews conducted by the senior managers of a number of major construction firms in Iran. More detailed information on the generation of the dataset can be found in Rashidi *et al.* (2011). Next, the importance of each criterion was determined quantitatively using a novel method, that is, the fuzzy curves method. In this way, the effects of changing the number of fuzzy rules and of eliminating a number of less important criteria were evaluated, and an optimized model that considers the least number of required criteria and gives an acceptable level of accuracy was selected. This optimized model was used in real interviews in a major construction firm. The results obtained will be compared with the results of traditional real interviews.

The rest of this paper is structured as follows: in section 2, the general structure of fuzzy expert systems is briefly described. In section 3, the general process for the development of a fuzzy system for solving the problem of selecting project managers in construction firms is presented. Section 4 contains the necessary steps for optimizing the initial fuzzy system, and describes the procedure for testing and validating the proposed model using test data. In section 5, the application of the proposed model in real interviews, which were conducted in a major construction firm, is shown. In the final section, conclusions are drawn and discussed.

2. Fuzzy systems

A fuzzy system is formed by input and output fuzzy sets assigned over the system input and output variables, and accumulated fuzzy rules. The relationships between the input and the output variables are represented by means of fuzzy IF–THEN rules of the following general form (Karaboga *et al.* 2008): "IF antecedent proposition, THEN consequent proposition".

The most significant advantage of using this linguistic description is that no prior knowledge about the system under study is initially used to formulate the rules, and the fuzzy system is constructed from data (Karaboga *et al.* 2008).

Generally, creating a fuzzy system consists of two basic steps:

I. For each variable input or output, a set of fuzzy sets must be defined. Each fuzzy set is itself defined using a fuzzy membership function. A membership function defines the degree to which the value of a variable belongs to the group and is usually a linguistic term such as "high" or "low." The quantitative value of the membership function varies from 0 to 1 (Plebankiewicz 2009).

For example, μ_{ij} is the jth membership function of the ith input variable (x_i) and defines the jth linguistic term for this input variable (A_{ij}); τ_k is the kth membership function of the output (y) and defines its kth linguistic term (B_k). A membership function is defined by its shape (type) and parameters. In the case of fuzzy systems, standardized functions are usually used.

II. Statements, or rules, are defined so that they relate the membership functions of each variable to the result, normally through a series of IF–THEN statements (Radziszewska-Zielina 2011). For example, in the context of problems in project manager selection, one rule would be as follows: IF the language ability of the candidate is low (linguistic term A_{11}, represented by a membership function μ_{11}), and the quality of the university where the candidate studied is low (linguistic term A_{21}, represented by a membership function μ_{21}) (condition), THEN the score of this candidate (conclusion) is low (linguistic term B_1, represented by a membership function τ_1) (Torno *et al.* 2011).

The rule is stated as follows:

IF x_1 is A_{11} and x_2 is A_{21}, THEN y is B_1.

In using the system, inputs are given to the system and an output is obtained. Further information can be found in Antonelli *et al.* (2009), Torno *et al.* (2011) and Du *et al.* (2008).

3. The initial fuzzy system for project manager selection

3.1. Gathering historical data

The first step in the construction of the fuzzy system is to determine the related criteria and sub-criteria for project manager selection. In order to do this, all criteria that may be considered by the senior managers of construction firms for project manager selection should be determined (Torfi, Rashidi 2011).

Table 1. Criteria and sub-criteria for selection of project managers

No.		Criterion	Possible options
1	Technical and professional background	Years of experience	0–45 years
2		Years of management experience	0–45 years
3		Years of experience with current employer	0–45 years
4		Years of experience in similar project fields	0–45 years
5		Years of experience working with project owner	0–45 years
6		Years of experience in similar project environments	0–45 years
7		Share holder or board member of the company?	Yes–No
8		Quality assessment of previous projects	0–100 points
9	Educational background	Major	Mechanical Engineering – Civil Engineering – Chemical Engineering – Electrical Engineering – Other
10		Degree	BS – MS – PhD
11		Quality of the university where the applicant graduated	0–100 points
12		Specialization	Design – Construction – Supervision – Management – Other
13		Continual professional development	0–200 h
14		General communication skills in English	0–100 points
15	Demographic features	Gender	Male–Female
16		Age	25–70 years
17		Physical and mental abilities	Healthy-Unhealthy
18		Physical appearance	0–100 points
19	General management abilities	Human resource management abilities (number of employees working under applicant's supervision)	0–500 persons
20		Communication skills	0–100 points
21		Sound decision making under pressure	0–100 points
22		Work performance	0–100 points
23		Project condition assessment and prediction	0–100 points

To determine the necessary criteria for selection of qualified construction project managers, a questionnaire was sent to the senior managers of 18 large companies involved in different areas of construction e.g. oil and gas, roads and highways, and residential construction projects. These managers were requested to determine all the criteria they consider in the procedure of selecting a construction project manager. Based on the opinions of these experts, 23 criteria were determined and divided into four groups (Table 1).

The next step in preparing fuzzy rules is to collect historical data regarding the fuzzy system's input and output. In this study, as in the authors' previous research, the data were gathered from 46 interviews previously conducted over a two-year period by the senior managers of a number of major construction firms in Iran. All the interviews were conducted by the companies' chief officers, as they were considered to be the people best qualified to make hiring decisions. They used the above-mentioned 23 criteria for the evaluations. The scores assigned to each candidate for each criterion and the total score of each candidate – which is the basis on which the best-qualified candidate will be selected – were identified by these experts. In many instances, a scale of 0 to 100 was used to evaluate qualitative criteria; each candidate received a rating on the basis of the experts' opinions. 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.

On the basis of the collected data, the system outputs and inputs were classified. Inputs were derived after comparing two candidates' features for each criterion, and output was the result of comparing the total point scores of these two candidates. Obviously, in cases where the output rate was greater than 1, the first candidate was considered to be better than the second one, and vice versa. The candidates were ranked, and Table 1 provides excerpts of the interviews and information vis-à-vis defined inputs and outputs. The number of records in the input-output data was 262; of these, 200 records were used to develop the system and 62 were used to analyze and validate it.

3.2. Preparation of the initial fuzzy system

Using MATLAB, one fuzzy rule was developed for each training datum. A fuzzy rule is developed for each datum by including a number of inputs and one output. The appropriate membership function for criteria for which there were multiple answers was either triangular or trapezoidal; for the remaining criteria, the appropriate membership function was Gaussian functions because they can approximate almost all other types of membership functions by changing the parameters shown in Eq. (1) (Lee, Pan 2009):

$$\delta = \exp(-\frac{(x-c)^2}{2\sigma^2}),\qquad(1)$$

where: δ is the degree of membership (membership value); c is the center of the membership function; and σ is the width of the membership function (standard deviation), which can be calculated according to Eq. (2) (Chao *et al.* 1996):

$$\sigma_{ij} = \frac{\max\left\{\left|c_{ij} - c_{iR}\right|\left|c_{ij} - c_{iL}\right|\right\}}{\sqrt{\left|\ln\lambda_i\right|}},\qquad(2)$$

where: A_{ij} is the jth fuzzy membership function of ith variable; σ_{ij} is the width of A_{ij}; c_{ij} is the center of A_{ij}; c_{iR} is the center of fuzzy membership function, which is on the right side of A_{ij} and is closest to it; c_{iL} is the center of fuzzy membership function, which is on the left side of A_{ij} and is closest to it; λ_I is the overlapping factor of ith variable ($0 < \lambda_i < 1$).

However, in cases where the sub-criterion (input) is a multiple-choice option (like educational level), the quantity c is low. In these cases, a Gaussian membership function cannot be used; instead, a triangular membership function can be used. Each quantity has a triangular membership function.

As an example, three possible membership functions for the 7th criterion are depicted in Fig. 2. For this criterion, for the statement "yes", the value is 2, and for the statement "no", the value is 1. There are therefore three options, i.e., 2 / 1 = 2; 2 / 2 = 1, and 1 / 2 = 0.5 (Fig. 1).

The fuzzification rules were defined on the basis of the historical data. In this case, $\lambda = 0.5$ for all Gaussian membership functions.
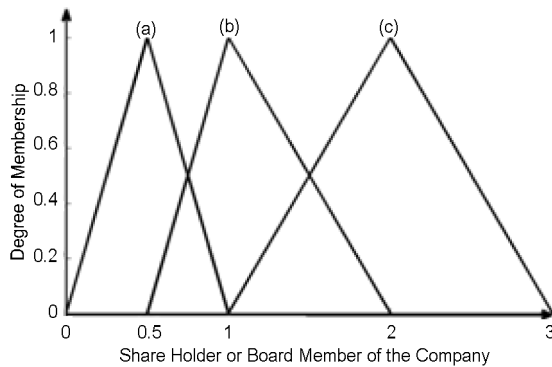

Fig. 1. Triangular membership functions of "share holder or board member of the company" sub-criterion (*a*) – $c = 0.5$, (*b*) – $c = 1$, (*c*) – $c = 2$

4. Simplification of the initial system using trial and error

One of the most important motivations for building up a fuzzy system is to let users gain a deeper insight into an unknown system through easily understandable fuzzy rules (Wang *et al.* 2005). Fuzzy systems can be interpreted for modeling unknown nonlinear environments (Jin

2000). Interpretability is a very important property, and those traditional training methods for extracting fuzzy rules that suffer from lack of interpretability have an unnecessary number of rules (Eftekhari *et al.* 2008). Accordingly, several studies on the interpretability of fuzzy systems in different fields have been carried out (Ishibushi *et al.* 2001; Liang, Pedrycz 2009). In this paper, a novel and efficient approach is presented for constructing a fuzzy system that considers both accuracy and interpretability. An appropriate approach, using a similarity approach, has been applied to simplify the fuzzy system using similarity analysis.

System simplification was carried out using the following two procedures:
1. Combining similar rules;
2. Removing insignificant inputs.

By performing these procedures, a compact rule-based system with low complexity and high accuracy can be achieved.

4.1. Combination of similar fuzzy rules

Constructing a system using data may result in a number of initial membership functions, some of which are similar to each other and which therefore result in some redundant rules. A rule is redundant when it does not alter the rule base (Dubois *et al.* 1997). Redundant rules decrease the system's ability to interpret, and therefore, similar rules should be combined (Du *et al.* 2008).

The concept of the redundancy of fuzzy rules can be expressed by measuring the similarity of fuzzy sets of inputs and outputs (Castellano *et al.* 2002; Guillaume 2001). The similarity between two fuzzy sets is the degree to which the fuzzy sets are equal (Setnes *et al.* 1998). There are a number of definitions of similarity measures (Jin *et al.* 1999; De Baets *et al.* 2009). In this study, the similarity measure proposed by Jin (2000) has been used:

$$S(A,B) = \frac{M(A\cap B)}{M(A\cup B)} = \frac{M(A\cap B)}{M(A)+M(B)-M(A\cap B)},\qquad(3)$$

where: $M(A)$ is the cardinality of the fuzzy set A, and $\cap$ and $\cup$ are the intersection and union operators, respectively. The cardinality of the fuzzy set A is expressed by Jin *et al.* (1999):

$$M(A) = \int_{-\infty}^{+\infty}\mu_A(x)dx.\qquad(4)$$

To determine whether two fuzzy rules should be combined, the degree of similarity of the fuzzy rules should be determined (Chao *et al.* 1996). If the similarity measure of two fuzzy rules is greater than a given threshold, then these two fuzzy rules should be combined to generate a new rule. In order to combine two fuzzy rules and obtain a new one, the input and output membership functions of two of the initial fuzzy rules should be combined. If c_1 and c_2 are the centers and σ_1 and σ_2 are the widths of the initial two fuzzy sets, then the center and width of the new fuzzy set can be determined according to Eqs (5) and (6) (Eftekhari *et al.* 2008):

$$c_{new} = \frac{\sigma_1 c_1 + \sigma_2 c_2}{\sigma_1 + \sigma_2}; \qquad (5)$$

$$\sigma_{new} = \frac{\sigma_1 + \sigma_2}{2}. \qquad (6)$$

If the initial membership functions are triangular with the parameters (a_1, b_1, c_1) and (a_2, b_2, c_2), the parameters of a new membership function can be determined according to Eqs (7–9):

$$a_{new} = \min(a_1, a_2); \qquad (7)$$

$$b_{new} = \frac{b_1 + b_2}{2}; \qquad (8)$$

$$c_{new} = \max(c_1, c_2). \qquad (9)$$

The procedure of combinig two fuzzy sets is shown in Fig. 2.

In the process of combining fuzzy rules, redundant rules may be eliminated from the rule base. At each iteration, the two rules whose similarities exceed the threshold should be combined. The rules obtained from these combinations are candidates for combination in the next iteration. The membership functions of these rules obtained by combination should therefore be assigned more weight in the merging process. More detailed information can be found at Paiva and Dourado (2004). In this study, five thresholds for the similarity measure of fuzzy rules (0.1, 0.09, 0.08, 0.07, and 0.06) were utilized. Hence, after simplifying the initial system, five systems with a diffe-

rent number of fuzzy rules (71, 62, 52, 48, and 43) were constructed.

4.2. Determining the most important criteria

In order to simplify the system, the importance of each sub-criterion should be determined, and insignificant criteria should be eliminated from the system so that the performance of the system is not affected. A precise fuzzy system is expected to accurately determine the most suitable person in a pair-wise comparison. In other words, for an actual output greater than 1, the system output should be greater than 1, and vice versa.

To rank the inputs (sub-criteria) according to their significance, fuzzy curves are plotted for all input variables. For each input variable x_i ($i = 1, 2, 3, …, n = 23$), the m data points in the x_i–y space are available. For every point in the x_{ij}–y_j space ($j = 1, 2, 3, …, m = 100$), a fuzzy membership function φ_{jk} and, consequently, a fuzzy membership value $c_j(x_i)$, can be calculated using the following formulas (Chaturvedi *et al.* 2009):

$$\phi_{jk}(x_i) = \exp(-(\frac{x_{ij} - x_{ik}}{b})^2); \qquad (10)$$

$$c_j(x_i) = \frac{\sum_{k=1}^{m} \varphi_{jk}(x_i).y_k}{\sum_{k=1}^{m} \varphi_{jk}(x_i)}. \qquad (11)$$

$$a_{new} = a_1, \quad b_{new} = \frac{b_1 + b_2}{2}, \quad c_{new} = c_2$$

$$c_{new} = \frac{\sigma_1 c_1 + \sigma_2 c_2}{\sigma_1 + \sigma_2}, \quad \sigma_{new} = \frac{\sigma_1 + \sigma_2}{2}$$
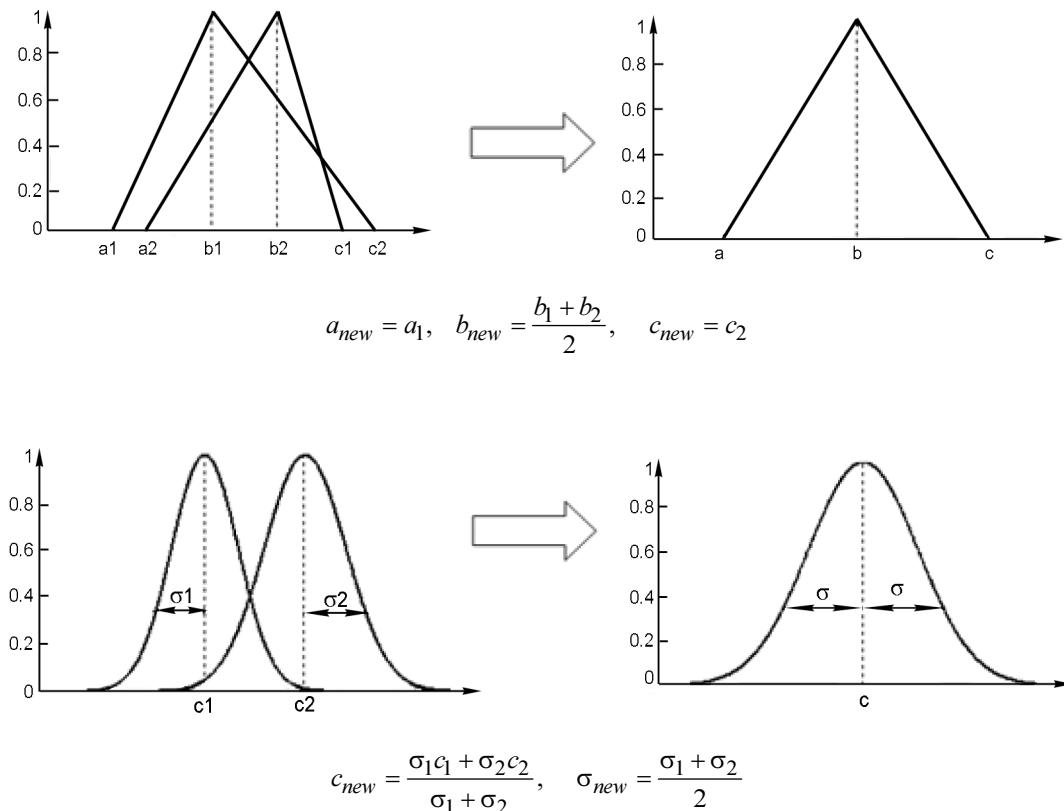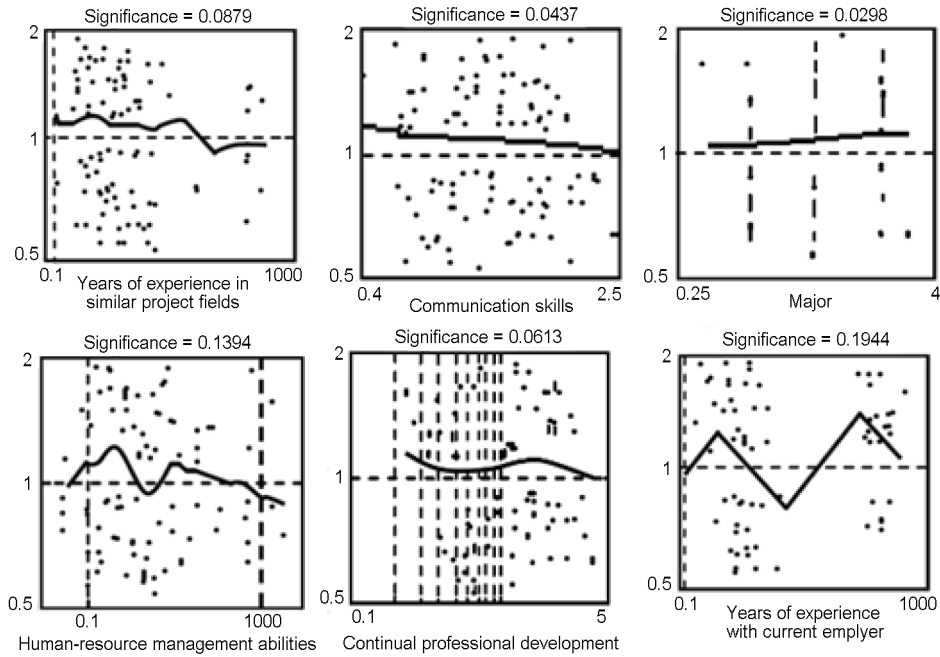
Fig. 2. Integration of fuzzy sets

Fig. 3. Samples of fuzzy curves for different criteria

The fuzzy curve for each input variable is plotted by taking x_{ij} on the *x*-axis and the corresponding $c_j(x_i)$ on the *y*-axis. The importance of an input variable can be ranked according to the range covered by its corresponding fuzzy curve. If the fuzzy curve for a given input is flat, then this input has little influence on the output data and it is not considered a significant input. Thus, the fuzzy correlation of the ith input to the output can be found from the difference between the maximum and minimum values of $c_j(x_i)$. Accordingly, the importance of the sub-criteria can be determined.

Fig. 3 depicts the fuzzy curves for 6 different sub-criteria as sample. Using the fuzzy curves, the significance of the criteria coefficients can be calculated. The results of this calculation are shown in Table 2.

Table 2. Coefficients of importance for different criteria

Number of criterion	W_j	Number of criterion	W_j
1	0.179	13	0.061
2	0.117	14	0.192
3	0.194	15	0.027
4	0.088	16	0.053
5	0.105	17	0.035
6	0.105	18	0.003
7	0.012	19	0.139
8	0.009	20	0.044
9	0.03	21	0.035
10	0.016	22	0.015
11	0.015	23	0.005
12	0.023		

4.3. Choosing the optimal system

After identifying the importance coefficients for all criteria, less important criteria (inputs) should be eliminated to obtain a simpler model. Generally, the lower the number of inputs, the greater is the number of model errors. Model errors were therefore defined for different numbers of inputs. This was conducted for different models with different numbers of rules. Furthermore, in order to evaluate the effect of the type of t-norm and t-co-norm, different models with different numbers of outputs, different numbers of fuzzy rules, and different types of norms and co-norms were developed and tested.

In this research, the equation suggested by Filev and Yager (1991) has been used for deffuzification:

$$\bar{y} = \frac{\int (\mu)^\alpha \, y dy}{\int (\mu)^\alpha \, dy}, \alpha > 0, \qquad (12)$$

where: μ is the degree of membership and α is a coefficient equal to one.

Table 3 shows the number of model errors in the selection of the most suitable candidate in pair-wise comparisons for 100 training data. It is clear that systems with different t-norms and t-co-norms have similar performances with minute differences. This indicates the minor effect of the type of t-norm and t-co-norm on the performance of the system. However, a combination of "algebraic product" and "max" would give optimal results. This combination was therefore used in the final system.

Obviously, the number of fuzzy rules and the number of criteria taken into consideration depend on the accuracy expected from the system.

In this case, a final system with 71 rules and 15 criteria was selected. The number of errors given by this system was 1 among 100 training data; this was considered to be an acceptable error rate. This means that from the initial 23 criteria, 8 were eliminated to simplify the model. The eliminated, less important criteria are: Physical appearance, Being share holder or board member of

Table 3. Number of errors for different systems in the selection of the most suitable candidate through pair-wise comparisons

Max			Min						Algebraic product				
			Number of rules						**Number of rules**				
	Number of criteria		71	62	52	48	43	Number of criteria	71	62	52	48	43
		10	2	3	4	5	5	10	2	3	3	4	5
		11	2	2	3	4	5	11	2	2	3	4	4
		12	2	2	3	3	5	12	2	2	2	3	4
		13	2	2	2	3	4	13	2	2	2	3	4
		14	2	2	2	3	4	14	2	2	2	2	4
		15	2	2	2	3	3	15	1	2	2	2	3
		16	1	2	2	3	3	16	1	1	2	2	2
		17	1	2	2	3	3	17	1	1	1	2	2
		18	1	2	2	3	3	18	1	1	1	2	2
		19	1	2	2	2	3	19	1	1	1	1	1
		20	0	1	1	2	3	20	1	1	1	1	1
		21	0	0	1	2	3	21	1	1	1	1	1
		22	0	0	0	2	2	22	0	0	0	0	1
		23	0	0	0	1	1	23	0	0	0	0	1
Algebraic sum			**Number of rules**						**Number of rules**				
	Number of criteria		71	62	52	48	43	Number of criteria	71	62	52	48	43
		10	3	3	5	5	5	10	3	3	4	5	5
		11	3	3	4	4	5	11	3	3	3	3	5
		12	3	3	3	4	5	12	2	3	3	3	4
		13	2	2	3	4	5	13	2	3	3	3	4
		14	2	2	2	3	4	14	2	3	3	3	3
		15	2	2	2	3	4	15	2	2	2	2	3
		16	2	2	2	3	3	16	1	2	2	2	2
		17	2	2	2	2	2	17	1	1	1	1	2
		18	1	1	1	1	2	18	1	1	1	1	2
		19	1	1	1	1	2	19	1	1	1	1	2
		20	1	1	1	1	1	20	1	0	0	1	1
		21	0	0	1	1	1	21	0	0	0	0	1
		22	0	0	0	1	1	22	0	0	0	0	1
		23	0	0	0	1	1	23	0	0	0	1	1

the company, Quality assessment of previous projects, Degree, Quality of the university where the applicant graduated, Specialization, Work performance and Project condition assessment and prediction.

5. Validation of the fuzzy system for selection of project manager

To evaluate the developed fuzzy model, the interviews conducted for the selection of a project manager were reviewed. As mentioned before, 62 data from the available dataset were considered. The model is expected to be sufficiently accurate to rank the participants in the interviews correctly. The results of this evaluation are presented in Fig. 4.

In the figure, the empty circles indicate the model responses and the filled circles indicate the desired responses. As can be seen, the model contains only one error in the pair-wise comparisons of participants (data item number 18). In the other 61 cases, the model responses and the desired responses are slightly larger or smaller than 1; in other words, in almost all pair-wise comparisons between the candidates, the most suitable candidate

is determined correctly. This indicates the model's potential to predict the right output, that is, the best candidate for the position of project manager.
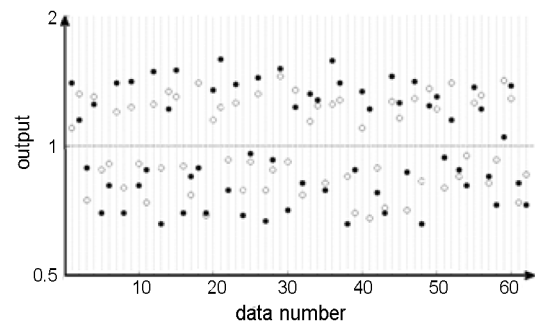

Fig. 4. Results of the evaluation of the model developed for selecting a project manager

6. Case study

To show how our model performs under real-world conditions, it was used in real interviews conducted by the senior managers of a major construction company. These interviews were conducted with seven candidates. The

candidates' scores in each criterion, as well as their overall scores determined on the basis of the interviewers' opinions, are shown in Table 4.

On the basis of the accumulated information in Table 4, pair-wise comparisons between candidates were performed using the new fuzzy system based on 15 criteria. The results obtained from the system and the actual results determined by the interviewers are summarized in Table 5.

As can be observed, the pair-wise comparisons were performed correctly, except in two cases. These two cases are the comparisons between the 4th and 6th pair of candidates and the 7th and 3rd pair (these two cases are highlighted in bold).

For these interviews, using the proposed system with 15 criteria, the required time to input the information for seven candidates and run the fuzzy system is less than 20 minutes. When using the old fuzzy system with all 23 criteria, the total time required is more than twice this – 40 minutes. In addition, gathering the information for 15 criteria is much faster and easier. Therefore, when there are a large number of candidates, the current system is recommended.

If a normal traditional interview takes 30 minutes, interviewing all seven candidates would require 210 mins. This comparison clearly indicates the advantage of using a fuzzy system with respect to the time needed. It is important to mention that to use the fuzzy model, we need to gather the candidates' information, which is a time-consuming task. However, this is not the duty of senior managers, and other staff could collect such data. Therefore, this time could be eliminated from the time required to run the model.

Table 4. Interviewees' information: comparisons of real-life interviews and fuzzy system cases

No.	Criterion	Status	1st candidate	2nd candidate	3rd candidate	4th candidate	5th candidate	6th candidate	7th candidate
1	Years of experience	0–45 years	27	21	12	9	28	14	9
2	Years of management experience	0–45 years	24	8	5	4	18	5	0
3	Years of experience with current employer	0–45 years	22	8	0	0	12	5	0
4	Years of experience in similar project fields	0–45 years	27	21	8	5	15	5	6
5	Years of experience working with project owner	0–45 years	0	5	0	0	6	9	0
6	Years of experience in similar project environments	0–45 years	5	15	4	4	15	5	3
7	Major	Mechanical Engineering Civil Engineering Chemical Engineering Electrical Engineering Other	4	3	4	4	4	4	3
8	Continuing professional development	0–200 h	70	110	90	40	80	150	50
9	General communication skills in English	0–100 score	85	80	55	55	85	70	65
10	Gender	Male (1) Female (2)	1	1	1	1	1	1	1
11	Age	25–70	55	55	45	35	54	38	24
12	Physical and mental abilities	Healthy (1), Unhealthy (2)	1	1	1	1	1	1	2
13	Human resource management abilities (number of employees working under applicant's supervision)	0–500 persons	100	80	30	40	450	200	10
14	Communication skills	0–100 score	85	35	60	55	90	70	70
15	Sound decision-making under pressure	0–100 score	75	65	65	60	80	80	55
	Final score	0–100 score	90	85	62	75	70	65	55

Table 5. Comparison of candidates: real results vs. model results

Comparison between candidates	1st/2nd	1/3	1/4	1/5	1/6	1/7	2/1	2/3	2/4	2/5	2/6	2/7	3/1	3/2
Model's output	1.2	1.4	1.3	1.2	1.6	1.3	0.7	1.1	1.4	1.1	1.6	1.2	0.9	0.9
Real output	1.1	1.5	1.2	1.3	1.4	1.6	0.9	1.4	1.1	1.2	1.3	1.5	0.7	0.7
Comparison between candidates	3/4	3/5	3/6	3/7	4/1	4/2	4/3	4/5	4/6	4/7	5/1	5/2	5/3	5/4
Model's output	0.7	0.8	0.6	1.3	0.7	0.7	1.4	1.4	1.3	1.1	0.6	0.7	1.2	0.7
Real output	0.8	0.9	0.9	1.1	0.8	0.9	1.2	1.1	1.2	1.4	0.8	0.8	1.1	0.9
Comparison between candidates	5/6	5/7	6/1	6/2	6/3	**6/4**	6/5	6/7	7/1	7/2	**7/3**	7/4	7/5	7/6
Model's output	1.3	1.4	0.6	0.9	1.3	**1.1**	0.7	1.1	0.7	0.8	**1.1**	0.7	0.7	0.9
Real output	1.1	1.3	0.7	0.8	1.1	**0.9**	0.9	1.2	0.6	0.6	**0.9**	0.7	0.8	0.8

7. Conclusions and discussion

The selection of a project manager from a set of potential candidates is an important, difficult, and time-consuming task for the senior managers of any construction company. This problem worsens with an increase in the number of candidates. There is also a risk of human error in judgment and decision making. On the other hand, not interviewing all the candidates may mean overlooking some qualified applicants. There is therefore a need for computational models that can increase the accuracy of decisions and reduce the time required.

Previously, the authors constructed a fuzzy system for the process of project manger selection in construction firms. This fuzzy system needs information for 23 criteria. Gathering the information from a large number of candidates for all 23 criteria is difficult and time consuming. Therefore, in this paper, a more robust fuzzy system is proposed to solve this problem. To perform accurately, the proposed system only needs information for 15 of the more important criteria. This helps to speed up the selection procedure significantly. The proposed model was developed on the basis of data accumulated from a number of interviews conducted in a number of major construction firms. The results obtained using the proposed model in real interviews show the model's ability to predict accurate outputs and its ability to reduce the time required for gathering data and running the system.

Unfortunately, although there are several existing studies, the application of decision-support systems in the construction industry is still in its initial stages. In our case, several factors that are difficult to take account of in the model-building process could affect the performance of the fuzzy model. For example, it is difficult to allow for psychological factors in the evaluation process. It might not always be possible to interview candidates extensively. There might be differences between internal and external candidates that must be accounted for. Finally, we still seem to lack good outcome data that can help us understand whether or not a choice that we make turns out to be a good one. Considering the limitations, the authors suggest using this model in two-stage interviews as follows:

− In the first stage, a limited number of candidates are selected;
− In the next stage, the chosen candidates are interviewed routinely and the most suitable one is selected by the interviewer.

In future studies, the authors intend to expand the current fuzzy system to a general model that can be used as a tool to assist in a vast range of interviews conducted in construction companies and other related firms.

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