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Increasing the Accuracy of Credit Risk Assessment of Contractors' Control System Using Fuzzy Logic Concepts and Multi-Objective Optimization Algorithm

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Abstract: - The credit risk of construction contractors is considered as a risk which arises from neglecting the contractor of the contracting party. This risk stems from the fact that the contractor of the contracting party cannot or will not fulfil the contract's obligations. The impact of this risk is measured by the financial and temporal burden caused by the contract of the construction contractor. Accurately measuring the credit risk of the contractors is considered as one of the most important factors for the survival and continuing the activities of construction contractor companies. This study aimed to introduce an expert model based on using fuzzy logic concepts and genetic optimization algorithm to challenge the credit risk assessment of contractors in the construction engineering contractors. The opinions of specialized managers at construction contractor companies were used after simulation to analyze the proposed genetic fuzzy system and the rate of error measurement of the credit risk of construction contractors was estimated by the fuzzy genetic system compared to other models and hierarchical analysis of the opinion of experts were calculated and compared in the construction area. The opinions of human factor were used to measure the credit risk of construction contractors, leading to a reduction in the accuracy of this risk assessment. There is a need for an optimal system for measuring credit risk due to the uncertain nature of each contractor's characteristics to measure the credit risk using the characteristics of each construction contractor at any time. The results indicated the success of the genetic fuzzy system compared to other models.

Keywords: Credit risk, contractor, fuzzy logic, genetic optimization, construction plan

Introduction

The credit risk management of construction contractors is considered as one of the important issues which should always be regarded in the construction contractor companies by these companies' managers [1]. Existing credit rating systems for construction contractors to manage and control the mentioned risk is considered as an undeniable necessity. Such a system determines the credit rating of construction contractors based on existing records and information, and categorizes them in terms of the amount of risk the construction contractor companies face with [2]. Benefiting from such a system helped construction contractor companies select their contractors and improve the level of productivity of the process of conducting operations of construction contractor companies while controlling and reducing credit risk [1]. Although this issue is important, a coherent and orderly process for determining credit risk, scoring, ranking, as well as determining credit ceilings based on the risk components is not considered in construction contractor companies in the field of allocating construction operations to contractors and the components are chosen mainly based on expert diagnosis and credit committee in these companies [1].

Providing construction and infrastructure operations is considered as one of the most important activities of construction contractor companies. The degree of validity and power of the operations with the desired amount and the specified time should be determined for the contractor applicants to perform these operations [3]. The chances that the applicant construction contractor carry out the assigned operations without financial and time burden with appropriate quality are known as the contractors' credit risk [1]. In addition, various models have been used so far to reduce the contractors' credit risk in construction contractor companies, one of the most important of which is using contractors' accreditation scoring model. The accuracy of measuring the components of this model (research problem) is considered as one of the most important challenges in using a

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credit scoring model in measuring the credit risk of contractors at construction contractor companies. The less human factors involved in measuring these values leads to greater accuracy of this model. Therefore, using expert models [4] such as the optimization algorithms [5] and fuzzy logic [6] in measuring the components of the credit scoring model components increase the accuracy of this model to measure the credit risk of construction companies' contractors, resulted in preventing financial and time overheads in such companies [7].

Regarding the problem and proposed research model, it is possible to increase the accuracy of measuring the risk and ultimately reduce the financial and time overheads in such companies through the genetic fuzzy system to measure the credit risk of contractors in construction contractor companies. Therefore, the accuracy of credit risk assessment of contractors in construction contractor companies and the amount of reducing financial and time overheads in this general company is regarded as the independent and dependent variables, respectively.

Literature review

Assessing the credit risk of construction contractors is considered as a framework through which construction contractor companies evaluate the probability of non-performance of the operations being assigned by the contractor and accredit him/her using the contractor's record [12]. Credit scoring is an objective instrument for the risk management which categorizes contractors based on statistics and information while the old models for evaluating contractors are mainly subjective and based on the view of the official (or officials) who delegate the company's operations [1]. In the current methods, the human factor opinions are used to measure the credit risk of construction contractors, leading to a reduction in the accuracy of measuring this risk. An optimal system for measuring credit risk is required due to the uncertain nature of each contractor's features. Cheng et al. used a hierarchical analysis model to evaluate contractors [14]. In addition, Kabir used fuzzy VIKOR model to verify contractors and consultants [13]. Sentil used a large verification model with multiple metrics benefitting from fuzzy TOPSIS model to integrate fuzzy hierarchical analysis with the fuzzy hierarchical analysis contractors [15]. Provin et al. used a fuzzy hierarchical analysis model to verify building industry contractors [8]. Potwin et al. provided a combined colony model of continuous ants and fuzzy set theory to allocate work to contractors [9]. Sander developed the web-based fuzzy evolutionary neural networks to estimate the performance of sub-contractor [10]. Ramesh proposed a model for developing a balanced scorecard model to evaluate contractors [15]. Similarly, Cheng et al. developed a combined fuzzy evolutionary neural network to increase the effectiveness of evaluating the contractor performance in the manufacturing industry [16]. Lee et al. provided a model for the qualification process of construction contractors through a fuzzy approach. Karaboga et al. used the ANFIS fuzzy neural network model to identify the customers who are eligible to get the loan [22]. The results were compared with linear differentiation regression which he collected their data from the financial institution for their evaluation and comparison. Lee et al. [2] provided a combined model consisting of a neural network and differentiation techniques for credit evaluation [23]. In this model, differentiation analysis is first used to construct a credit measurement model and then its outputs are used as inputs to the artificial neural network [23]. Mir Jalili et al. used 4-phase-neural and fuzzy-genetic classifiers to assess validity [24]. The model is evaluated based on community validated data from other studies [24]. Ivasezkooh et al. measured credit in small financial companies through utilizing fuzzy adaptive network (FAN) [25]. First, credit measurement data are displayed by fuzzy numbers, and then the FAN network is constructed based on inferential rules, which are 27 fuzzy rules. Finally, the network is taught through fuzzy numerical training data or the training process is performed on it. Anpola et al. used fuzzy logic and analysis based on soft calculations to evaluate the credit risk of commercial companies. The language variables used in the model are sustainability, customers' empowerment, customer literacy level, etc. [19].

Nakami et al. (1985) designed and introduced a framework for expert systems in bank credit management [19]. Further, Ganji et al. designed the expert system through Lisp language, which was used to assess the credibility of bank contractors. The database of this system originated from the theory of early credit risk management. The system was designed and implemented by the Fairclough Academy of Economics in Poland. This expert system followed the backwards-chaining method. In this method, it started with the ultimate goal of credit and reached the primary data, i.e. the applicant's data by passing the right rules (27). Bryant et al. designed an expert system called “Alice” to assess the facilities the agricultural projects [18]. Walker et al. designed the CEEES expert system to validate bank credit payment [20]. The system, written in Prologue, divided applicants into two eligible and non-eligible categories for receiving bank credits. [28]

Various models for measuring the contractors' credit risk have been introduced in construction contractor companies, among which the most important models were examined through expert systems to measure the credit risk of contractors and customers. As mentioned, reducing human intervention in decision- making and improving the accuracy of credit risk measurement models in construction contractor companies for selecting a contractor to human decision logic is considered as a very important step to reduce complexity and increase accuracy in these models.

Method

A conceptual model of designing, producing, and using the proposed genetic fuzzy system to measure the credit risk of construction contractors is presented to better understand this section. Figure 1 shows this conceptual model.

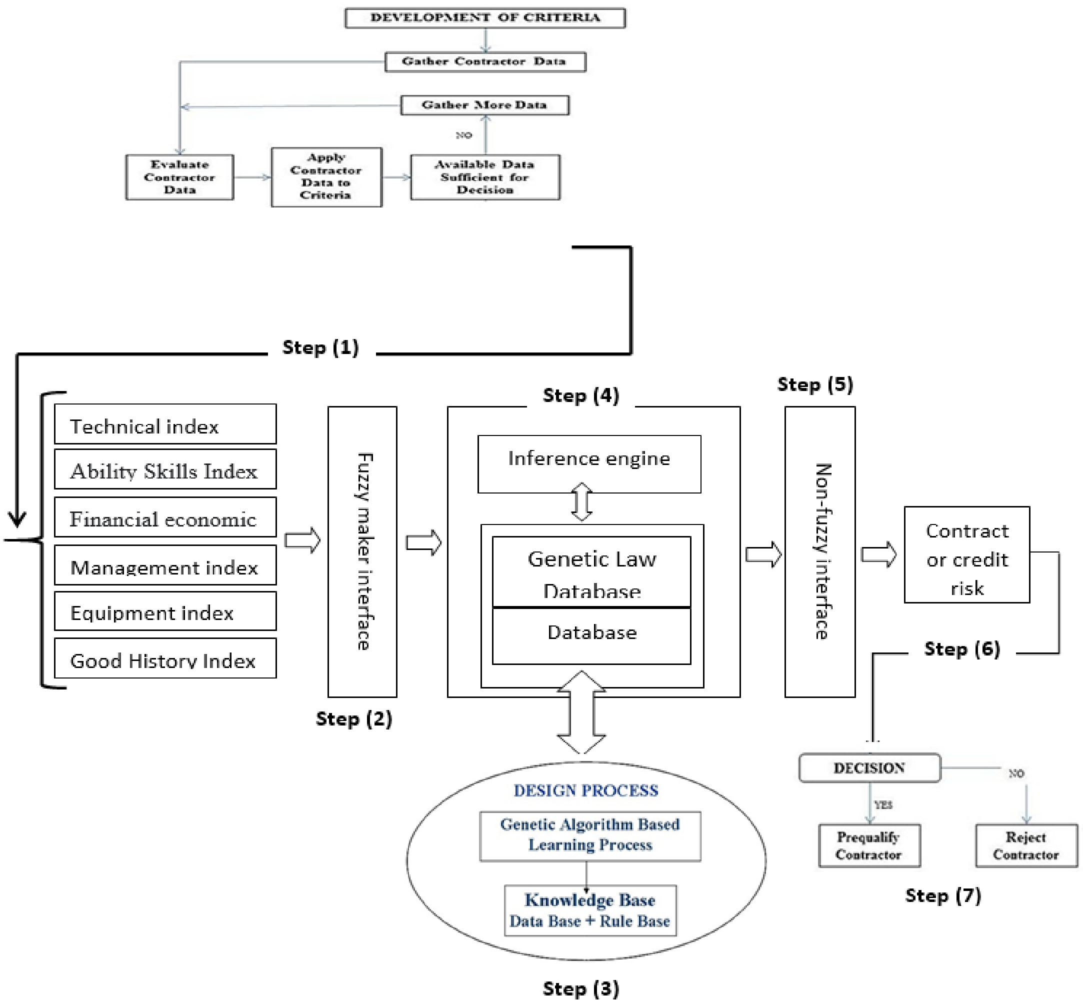


Figure 1 Conceptual model of the design process, production and how to use the proposed fuzzy genetic system research

As shown, different steps should be implemented in the process of designing, manufacturing, and using the genetic fuzzy system, which is reviewed as follows:

Step 1: The initial data of the contractors including the main and sub-components of the research are collected, evaluated, classified, and provided to the proposed genetic fuzzy system to measure credit risk.

Step 2: The main and sub-components prepared in the previous step are sent as input to the proposed genetic fuzzy system and the fuzzy interface to be converted from the definite state of the components to this system fuzzy.

Step 3: The rules and functions of the optimal membership of the proposed fuzzy system are extracted by the genetic optimization algorithm through the collected data and sent to the information database of this system for fuzzy inference.

Step 4: The fuzzy inference is made to measure the credit risk of contractors through the membership functions and optimal rules extracted in the previous step by genetic algorithm and the results are delivered to the non-fuzzy interface for converting from fuzzy mode to definite mode.

Step 5: The results are finalized by the non-fuzzy interface and the credit risk of the contractors is introduced as the output of the proposed genetic fuzzy system.

Step 6: The construction projects management team makes a decision on assigning the projects to the contractors through the credit risk for contractors extracted by the proposed genetic fuzzy system.

Step 7: The management team of the construction projects recognizes those contractors as incompetent and allocates their construction projects to the qualified construction contractors to be executed while concluding the contract if the contractors are recognized as non-qualified.

Simulating genetic fuzzy system

The genetic fuzzy system is introduced for the first time in the related field to measure the credit risk of construction contractors. Regarding the application of the designed genetic fuzzy system, the five steps for designing and simulating this system were considered to measure the credit risk of construction contractors as follows:

Step 1: Identifying the input and output variables of the genetic fuzzy system

After finalizing the conceptual model of the genetic fuzzy system, the input and output variables of the system were defined. Figure 2 shows the input and output variables of the genetic fuzzy system to measure the credit risk of life contractors.

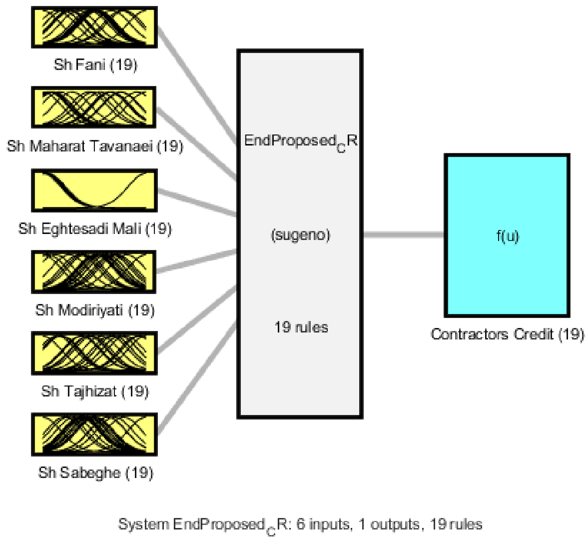


Figure 2. Linguistic variables of input and output of fuzzy genetic genetic research system

Step 2: Defining language variables and assigning fuzzy numbers and sets and membership functions.

The type of membership functions, the components of each membership function, and the range of changes of each membership function should be specified to design membership functions in the genetic fuzzy system. All of the requirements for designing the membership functions of the genetic fuzzy system were designed by the genetic optimization algorithm. The Gaussian membership function is used according to Equation (1) for linguistic variables (components of credit risk assessment of construction contractors) in the genetic fuzzy system.

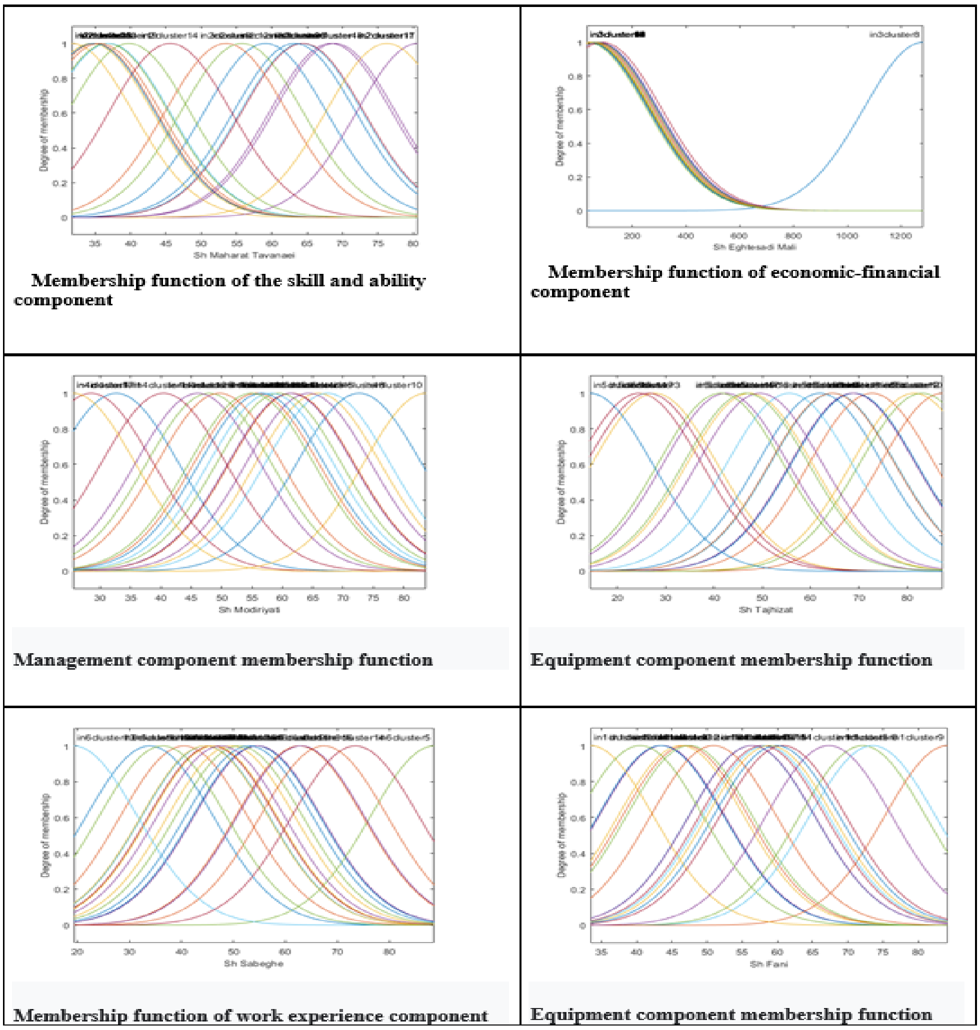
Equation (1)

$$\begin{cases} \exp\left[-\frac{1}{2} - \left(\frac{x-m_1}{\sigma_1}\right)^2\right], & x \le m_1 \\ 1 & otherwise \end{cases}$$

$$f_1\ (x) = \begin{cases} \exp\left[-\frac{1}{2} - \left(\frac{x-m_2}{\sigma_2}\right)^2\right], & otherwise \\ 1 & x \le m_2 \end{cases}$$

$$\mu\ (x) = f_1\ (x) * f_2\ (x)$$

Figure 3 displays the proposed Gaussian membership functions in the MATLAB environment for language variables (credit risk assessment components of construction contractors) in the genetic fuzzy system.



Membership function of the skill and ability component

Membership function of economic-financial component

Management component membership function

Equipment component membership function

Membership function of work experience component

Equipment component membership function

Figure 3: Proposed membership functions for linguistic variables (components of credit risk assessment of construction contractors) in the genetic fuzzy system of research

As shown, in the membership function diagrams, the X-axis represents the value of each point of the membership functions, and the Y-axis indicates the dependence (value) of each point on the X-axis, which is set between 0 and 1, and can have any value in the range of (0, 1). Selecting the optimal membership functions along with its components plays a very important role in the efficiency of each fuzzy inference. Then, the optimal values of these components were extracted through the genetic optimization algorithm.

Step 3: Designing the knowledge base of the genetic fuzzy system

As mentioned, the knowledge base in the fuzzy systems consists of a set of fuzzy rules. The fuzzy rules used in this study are Sugeno's fuzzy rules, which include an n preposition and a successor as shown in Equation (2).

Equation (2)

$$R_j : \text{If } X_1 \text{ is } A1_j \text{ and } \ldots \text{ and } Xn \text{ is } An_j \text{ Then Construction Contractors Credi Cluster } C_j t$$

As shown, $X = [X_1, X_2, \ldots, X_n]$ is an n-dimensional sample vector of the contractors' validation components, Aij (i = 1, 2, . . . , n) is the preliminary linguistic values (Values of contractors' validation components), Cj indicates the label of the contractor's credit cluster according to the R_j rule, which is considered as successor. A set of fuzzy rules in the form should be produced as Equation (2) to design the knowledge base of the fuzzy genetic contractor system. First, each attribute changes the value in the range [0 1]. Then, the sample space is subdivided into spaces, each known by a fuzzy rule. The degree of compatibility of each X_p sample with the preferential of a fuzzy rule is determined in the genetic fuzzy system as Equation (3).

Equation (3)

$$\mu_j\,(X_p) = \prod_{i=1}^{n} \mu_{ji}\,\left(x_{pi}\right)$$

In Equation (3), $\mu_{ji}(.)$ indicates the fuzzy set membership function.

Step 4: Designing the inference engine of the genetic fuzzy system

In the genetic fuzzy system, the inference process combines the information provided with the fuzzy rules of the sample to be clustered to determine the cluster of the sample. The most popular function of the fuzzy inference in fuzzy systems is the single winner rule based-inference [21]. A new sample Xp=[Xp1,Xp2,...,Xpn] with this model is classified as Equation (4).

Equation (4)

$$\mu_w\,(X_p) = \max\{\mu_j\,(X_p) : j = 1, 2, \ldots, N\}$$

The process of fuzzy inference in the genetic fuzzy system is examined [11] (Figure 4). In addition, the center of gravity method is selected for de-fuzzy to convert fuzzy numbers and sets to a definite value for examining the performance of the genetic fuzzy model accurately. Equation (5) shows the defuzzification of the genetic fuzzy model based on the center of gravity method.

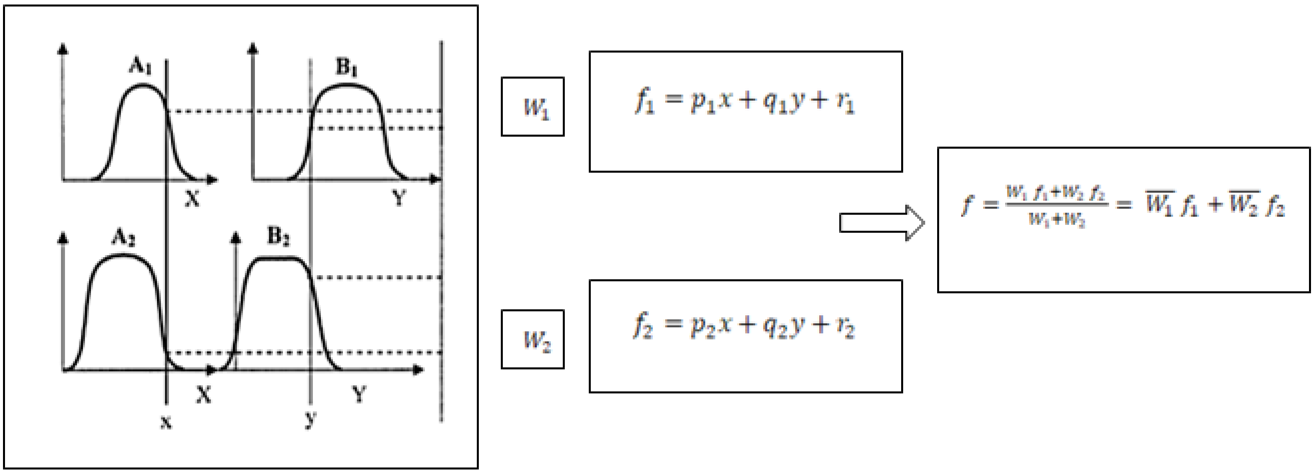


Figure 4. How to infer fuzzy in the genetic fuzzy system of research

Equation (5) shows the defuzzification of the genetic fuzzy model based on the center of gravity method.

Equation (5)

$$COG = \frac{\int_a^b \mu_A(x).x \quad dx}{\int_a^b \mu_A(x) \quad dx}$$

Step 5: Explaining how to use the genetic fuzzy system and analyzing its outputs

The outputs of the fuzzy genetic system are numerically (accurately) and linguistically analyzed to investigate the behavior of the output variable "The degree of credibility of construction contractors" in the genetic fuzzy model. Figure 5 analyzes the behavior of the input and output variables of the genetic fuzzy model.

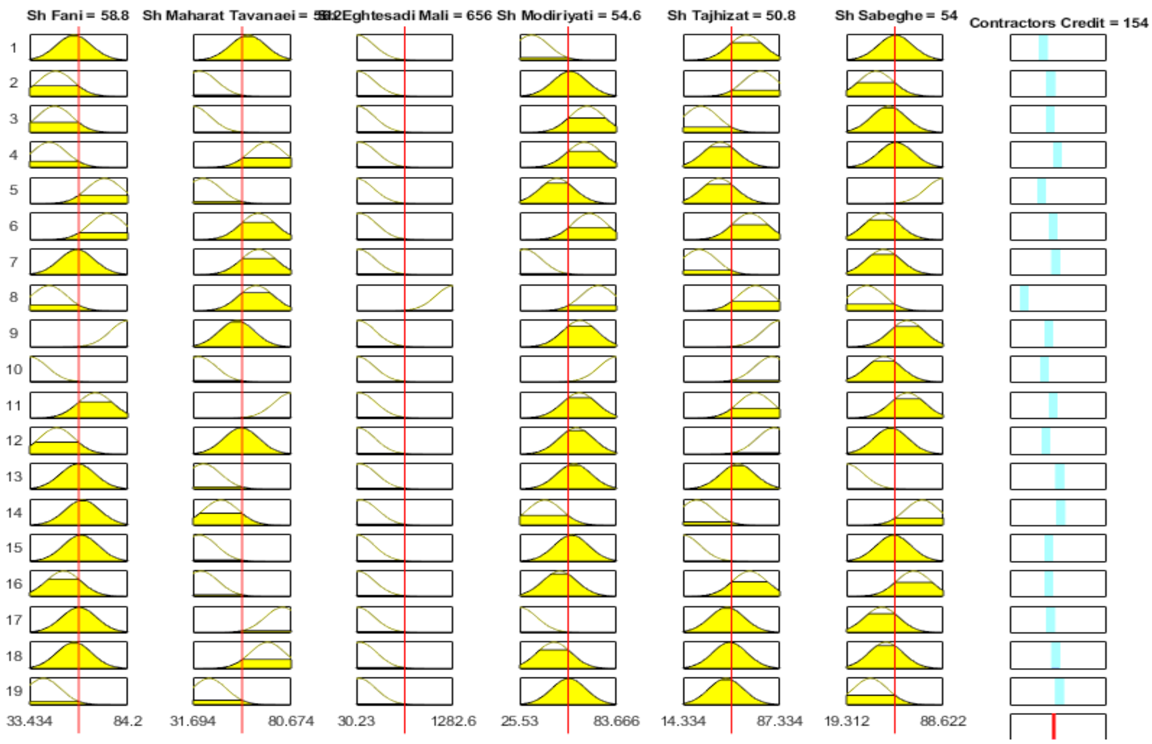
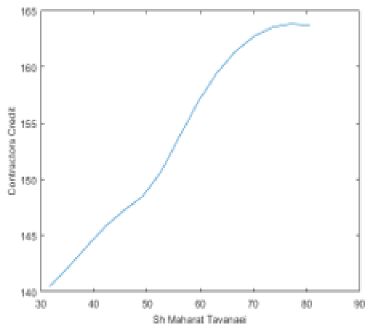
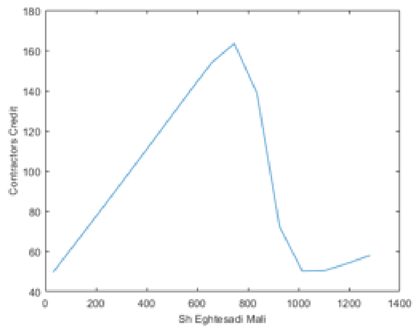


Figure 5 Analysis of the output variable behavior of "Construction Contractors' Credibility" numerically and linguistically based on input variables

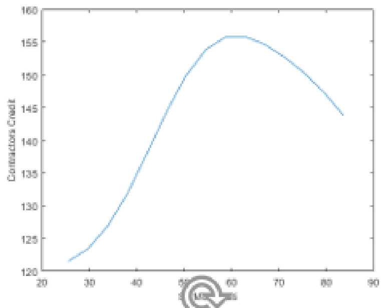
The surface diagram of the fuzzy genetic model is extracted through the MATLAB software used in designing this model to examine the general view of the genetic fuzzy model designed to solve the credit risk assessment problem of construction contractors.



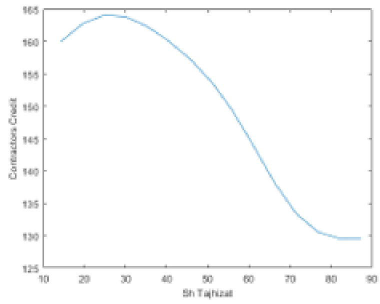
Surface diagram of skill and ability component



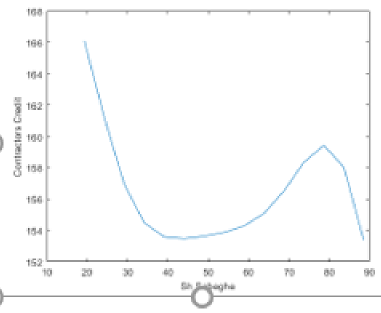
Surface diagram of financial economic component



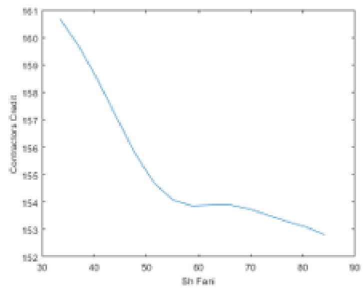
Surface diagram of the management component



Surface diagram of the equipment component



Surface diagram of work history component



Surface diagram of the technical component

Figure 6. A surface view of the input and output components of the genetic fuzzy model of the research

As shown in Figure 6, axis Y is the level of credibility of contractors to receive development projects, and axis X is the inputs of the genetic fuzzy system, i.e. the components of measuring the credit risk of construction contractors.

Findings

Data analysis

The determining components of the contractors' credit risk for using in the fuzzy genetic model were categorized into six types of linguistic variables. Then, the data presented in Table 1 provide the genetic fuzzy model and the Rao_CCPQ, Li_OCICS and hierarchical analysis models and the expert managers of construction contractor companies.

Table 1 Data table

Number of managers specializing in accreditation	Number of sub-components	Main components	Number of construction contractors
6	5	Technical component	20
6	6	Skill and ability	20
6	5	Financial Economics	20
6	6	Management and specialization	20
6	2	Equipment	20
6	4	Work Experience	20

Assessing the credit risk of construction contractors in the fuzzy genetic model

The information and components provided by the contractors were sent to the genetic fuzzy model as input. Then, the fuzzy was inferred in the model through the fuzzy membership functions and rules obtained by the genetics optimization algorithm, and the results of credit risk assessment for each contractor were presented as the output of the genetic fuzzy model.

Table 2 Results of credit risk assessment of construction contractors in the fuzzy genetic model of research

Credit risk	
Fuzzy genetic model of research	Contractor number
48.23597	1
53.59593	2
51.05	3
61.4031	4
53.39579	5
45.34386	6
56.30003	7
60.54772	8
72.67364	9
50.11583	10
48.552	11
62.99976	12
54.90125	13
52.51001	14
52.69211	15
62.31403	16
56.74266	17
57.43989	18
61.00801	19
71.85112	20

Figure 7 Results of construction contractors' credit risk assessment in the fuzzy genetic model of research

As shown in Figure 7, the components of each linguistic variables are sent to the inference engine of the research model and then the results obtained from this inference engine are de-fuzzified and the credit risk of the fuzzy genetic model obtained for each contractor is presented in Figure 7. For example, Table 2 indicates that the credit risk considered by the fuzzy genetic model for Contractor No. 10 is equal to 50.11583%.

Then, the credit risk assessment of construction contractors is extracted to analyze the credit risk of the fuzzy data model in the hierarchical analysis model [1], the results of which are used to compare the credit results of the fuzzy genetic model.

Assessing the credit risk of construction contractors in the hierarchical analysis

The credit risk in the hierarchical analysis model [1] was examined [1] through the presented materials to compare the contractors' credit risk with the values and components that determine credit risk in the hierarchical analysis model [1]. First, the determining components of the desired credit risk should be weighed and graded for each contractor. After weighing and grading all the components and sub-components, the credit intended for contractors in the analysis data set is extracted according to Table 3 and Figure 8, and is used in analyzing the analysis results.

Table 3. The results of measuring credit risk of construction contractors in the hierarchical analysis model

Credit Risk	
Hierarchical analysis model	Contractor No
57.1	1
62.1	2
64.1	3
63.1	4
53.1	5
45.1	6
55.1	7
49.1	8
49.1	9

51.1	10
46.1	11
59.1	12
59.1	13
55.1	14
51.1	15
61.1	16
56.1	17
64.1	18
62.1	19
52.1	20

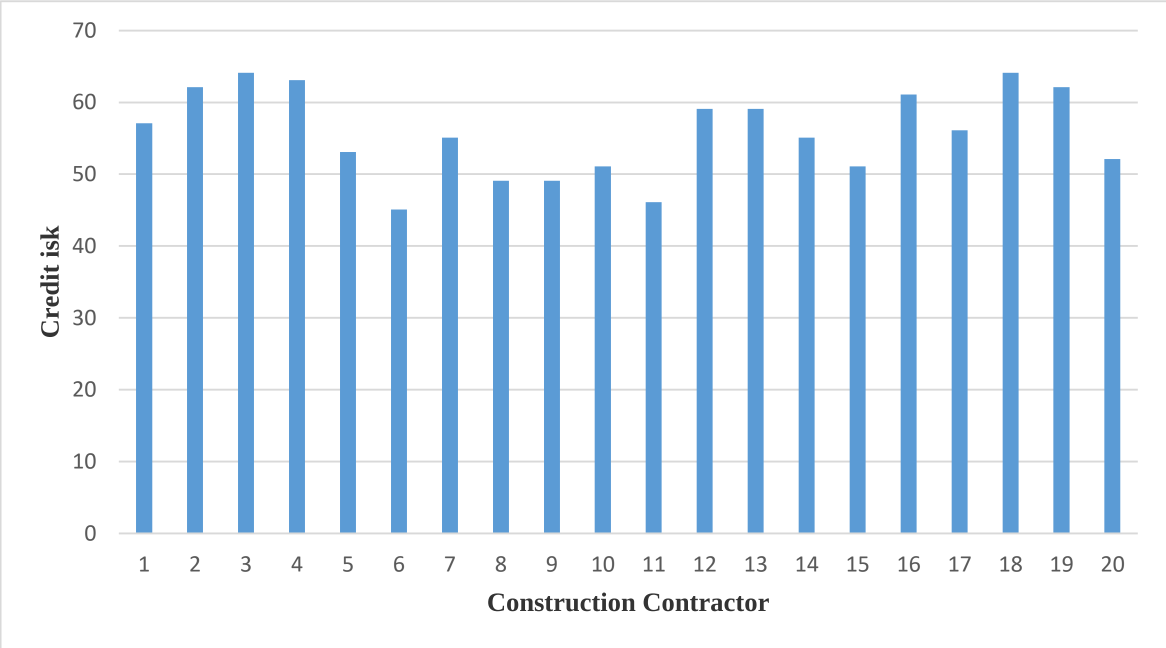


Figure 8. The results of measuring credit risk of construction contractors in the hierarchical analysis model

For example, the credit risk considered by the hierarchical analysis model [1] for contractor No. 10 is equal to 51.1%, as indicated in Table 3.

The credit risk assessment of construction contractors was extracted for collecting analytical data in the Li_OCICS model [91], the results of which are used to compare the credit results of the fuzzy genetic model.

Assessing the credit risk of construction contractors in Li_OCICS model

The credit risk of contractors was calculated based on the determining values and components of the credit risk in Li_OCICS model [91]. Finally, the amount of credit intended for contractors in the analysis data set according to Table 4 and Figure 9 was finally extracted in the [91] Li_OCICS model to measure the credit risk of construction contractors and was used in analyzing the analysis results.

Table 4: The results of measuring the credit risk of construction contractors in the Li_OCICS model

Credit Risk	
Li_OCICS Model	Contractor No
55.1	1
51.1	2
57.1	3

60.1	4
59.1	5
47.1	6
61.1	7
45.1	8
53.1	9
59.1	10
60.1	11
52.1	12
59.1	13
62.1	14
49.1	15
47.1	16
49.1	17
52.1	18
50.1	19
63.1	20

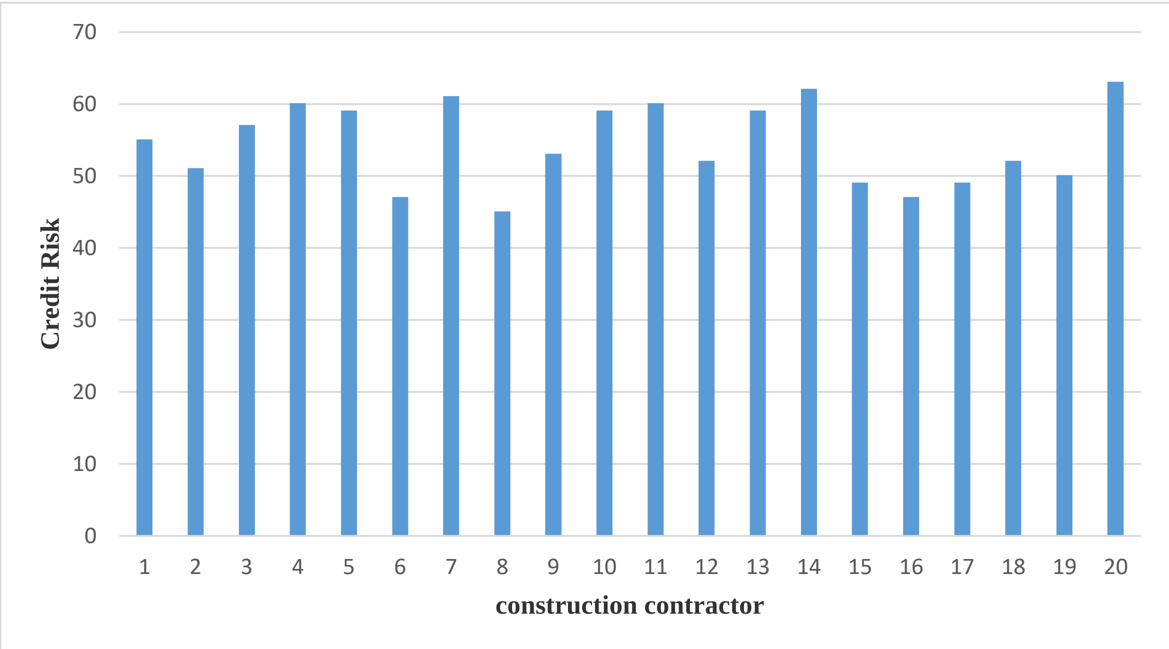


Figure 9. The results of measuring credit risk of construction contractors in the Li_OCICS model

For example, the credit risk considered by the Li_OCICS model [91] for contractor No. 10 is equal to 59.1 % as indicated in Table 4.

Then, the credit risk assessment of construction contractors is extracted to analyze the credit risk of the fuzzy data model in the Rao_CCPQ analysis model [84], the results of which are used to compare the credit results of the fuzzy genetic model.

Assessing the credit risk of construction contractors in Rao_CCPQ model

The credit risk of contractors was calculated based on the determining values and components of the credit risk in Rao_CCPQ model [84]. Finally, the amount of credit intended for contractors in the analysis data set according to Table 5 and Figure 10 was finally extracted in the Rao_CCPQ model [84] to measure the credit risk of construction contractors and was used in analyzing the analysis results.

Table 5: The results of measuring the credit risk of construction contractors in the Rao_CCPQ model

Credit Risk	
Rao_CCPQ Model	Contractor No
47.85084	1
52.33357	2
47.87051	3
58.43145	4
48.54424	5
46.7175	6
50.20544	7
55.83079	8
66.78531	9
46.89055	10
46.80264	11
65.95881	12
52.55932	13
46.99505	14
48.15438	15
56.72802	16
53.92424	17
54.82819	18
60	19
67.48478	20

Figure 10. The results of measuring the credit risk of construction contractors in the Rao_CCPQ model

For example, the credit risk considered by the Rao_CCPQ model [84] for contractor No. 10 is equal to 46.89055 % as indicated in Table 5.Then, the credit risk assessment of construction contractors is extracted to analyze the credit risk of the fuzzy data model in the expert managers analysis, the results of which are used to compare the credit results of the fuzzy genetic model.

Assessing the credit risk of construction contractors by Expert Managers

The credit risk of contractors was calculated based on the determining values and components of the credit risk by construction experts (by designed questionnaires). Finally, the amount of credit intended for contractors in the analysis data set according to Table 6 and Figure 11 was finally extracted by construction experts to measure the credit risk of construction contractors and was used in analyzing the analysis results.

Table 6: Results of credit risk assessment of construction contractors by expert managers

Credit Risk	
Construction expert managers	Contractor No
47.236	1
50.596	2
50.05	3
57.402	4
49.396	5
43.344	6
52.3	7
57.548	8
67.674	9
47.116	10
43.552	11
60	12
52.9	13
49.51	14
50.692	15
57.314	16
53.742	17
55.44	18
58.02	19
67.852	20

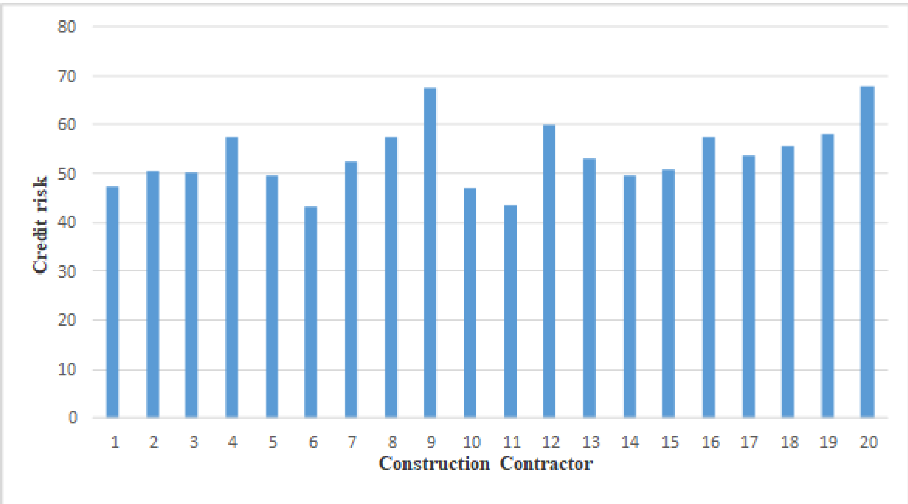


Figure 11. Results of credit risk assessment of construction contractors by expert managers

For example, Figure 11 shows that the credit risk considered by construction experts for Contractor No. 10 is equal to 47.116%. Then, the credit risk considered for the contractors in the analysis data set in the compared models is calculated and presented in Table 7 and Figure 12.

Table 7: Credit risk of construction contractors for the analysis data set in the compared models

Credit Risk					**Contractor NO**
Expert Construction	Fuzzy Genetic Model	Rao_CCPQ Model	hierarchical analysis	Li_OCICS Model	
47.236	48.23597	47.85084	57.1	55.1	1
50.596	53.59593	52.33357	62.1	51.1	2
50.05	51.05	47.87051	64.1	57.1	3
57.402	61.4031	58.43145	63.1	60.1	4
49.396	53.39579	48.54424	53.1	59.1	5
43.344	45.34386	46.7175	45.1	47.1	6
52.3	56.30003	50.20544	55.1	61.1	7
57.548	60.54772	55.83079	49.1	45.1	8
67.674	72.67364	66.78531	49.1	53.1	9
47.116	50.11583	46.89055	51.1	59.1	10
43.552	48.552	46.80264	46.1	60.1	11
60	62.99976	65.95881	59.1	52.1	12
52.9	54.90125	52.55932	59.1	59.1	13
49.51	52.51001	46.99505	55.1	62.1	14
50.692	52.69211	48.15438	51.1	49.1	15
57.314	62.31403	56.72802	61.1	47.1	16
53.742	56.74266	53.92424	56.1	49.1	17
55.44	57.43989	54.82819	64.1	52.1	18
58.02	61.00801	60	62.1	50.1	19
67.852	71.85112	67.48478	52.1	63.1	20

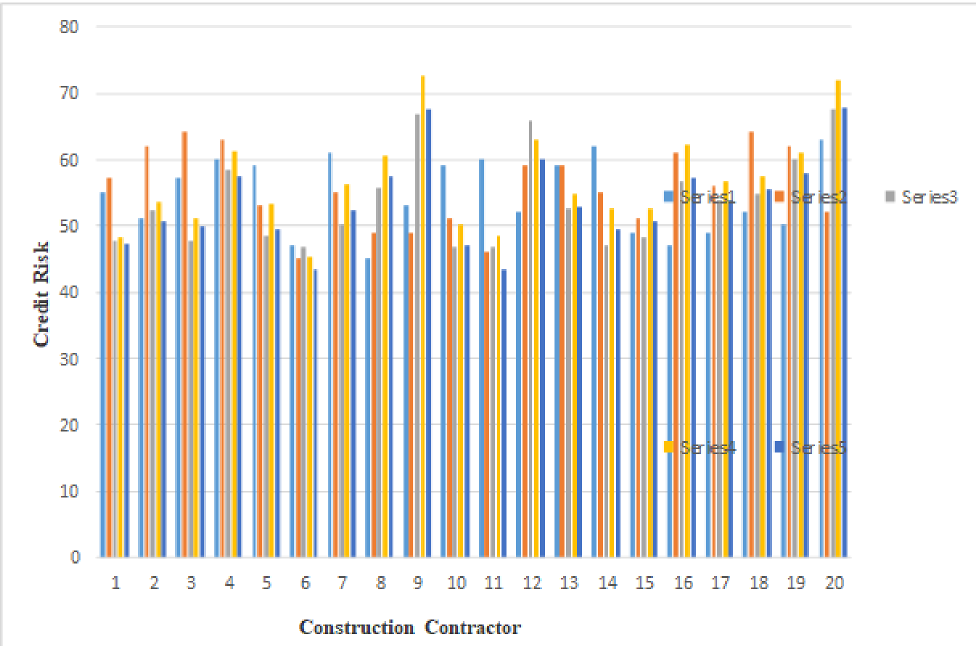


Figure 12 Credit risk of construction contractors for the analysis data set in the compared models

As shown in Figure 12, the credit risk considered for contractors in the fuzzy genetic model has a smaller deviation compared to those of Rao_CCPQ, Li_OCICS and hierarchical analysis models compared to the credit risk considered by specialized managers of construction companies.

Conclusion

During the recent years, there was the loss of many financial resources due to the incorrect selection of contractors in the construction industry. Proper introduction and selection of a contractor from among the verified contractors are considered as one of the key strategies for such problems. Therefore, choosing the right contractor is considered as one of the most important issues in implementing construction projects, ensuring that the risk of wasting resources, both in terms of cost and time, are minimized through choosing the right one. In addition, the projects have the highest quality of implementation and safety during or after implementation.

It was found that the proposed model aims to select the best contractors according to all the criteria. Further, it is a multi-criteria fuzzy model using genetic algorithms, the results of which indicate the success of the genetic fuzzy system than the compared models, as well as the ability to produce comparative results compared to other methods. Similarly, the experimental results indicated that the proposed method is effective and is considered as one of the best executive methods to measure the credit risk of construction contractors in municipalities and other centers which are related to the contractors.

The following suggestions are provided for future research:

1. Multi-criteria decision-making methods should be used.

2. Quantitative and qualitative indicators should be used simultaneously.

3. This model is performed by pairwise comparison method and the results of its case study are examined with the results of this research.

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