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Contractor Selection for Construction Project: A Genetic Fuzzy Model Approach

Abstract: **-** The selection of a contractor is a pivotal aspect in civil engineering projects, determining their success and efficiency. This article introduces a comprehensive multi-criteria model aimed at selecting the most suitable contractor by considering both qualitative and quantitative factors essential in contractor evaluation. Addressing the challenge of assessing credit risk among contractors in civil contractor firms, an expert model integrating fuzzy logic principles and a genetic optimization algorithm is proposed. Utilizing MATLAB software, the model is simulated, and the credit risk estimation accuracy is evaluated through expert opinions from construction employer companies. Metrics such as MRE, MMRE, VAF, VARE, and MARE are computed and compared with existing models including Rao_CCPQ, Li_OCICS, and hierarchical analysis, employing the Friedman test via SPSS software. Analysis reveals significant enhancements in these metrics within the proposed genetic fuzzy system compared to other models, indicating improved accuracy in credit risk assessment of construction contractors. Consequently, this improvement enhances validation accuracy of contractors, mitigates the risk of contractual default in construction employer companies, and prevents potential financial and temporal burdens in civil projects.

Keywords: Contractor selection, Multi-criteria model, Fuzzy logic, Genetic optimization algorithm, Credit risk assessment.

INTRODUCTION

Contractor selection is a critical issue in every civil engineering project, playing a fundamental role in its success. Therefore, identifying and evaluating a series of contractor selection criteria can eliminate inefficient contractors and choose the most suitable contractor for project implementation. This paper presents a multi-criteria model that, by considering all qualitative and quantitative factors affecting the evaluation of contractors, can select the best contractor for project execution. To address the challenge of assessing credit risk among contractors in civil engineering client companies, an expert model based on the use of fuzzy logic concepts and genetic optimization algorithms is proposed in this article. After conducting simulations and analyzing the proposed genetic fuzzy system, the opinions of expert managers from civil engineering client companies are utilized to estimate the level of credit risk assessment error among civil engineering contractors compared to Rao_CCPQ, Li_OCICS, and Hierarchical Analysis models. This comparison is performed using metrics such as MRE, MMRE, VAF, VARE, and MARE, as well as the Friedman test using SPSS software. The results of the analysis indicate an improvement in the level of these metrics in the proposed genetic fuzzy system compared to the models under comparison. This improvement signifies an increase in the accuracy of credit risk assessment among contractors in civil engineering client companies, ultimately reducing the risk of contractors' failure to fulfill their commitments and preventing financial and time burdens in civil engineering projects.

Assessing credit risk is of paramount importance across various industries, particularly in the construction sector where financial stability significantly impacts project success. This study delves into the evaluation of credit risk for construction contractors by conducting a thorough analysis utilizing multiple models. The research findings stem from an intricate examination of data employing the Genetic Fuzzy Model, the Rao_CCPQ Model, the Li_OCICS Model, and the Hierarchical Analysis Model, supplemented by insights from expert managers within construction contractor companies.

The study initially identifies six categories of linguistic variables crucial for determining credit risk in construction contractors. These variables encompass technical proficiency, skill and ability, financial economics, management and specialization, equipment, and work experience. Data analysis involves employing various models to assess credit risk, including the Genetic Fuzzy Model, which utilizes fuzzy inference and genetic optimization algorithms. Results from the Genetic Fuzzy Model illustrate the credit risk assessment for each contractor, providing valuable insights into their financial stability. Subsequent analyses through the Hierarchical Analysis, Li_OCICS, and Rao_CCPQ models further enrich the understanding of credit risk, enabling a comprehensive comparison across different assessment methodologies.

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Contractor selection is a critical process in construction projects, significantly impacting project success and performance. Various methodologies have been proposed to aid in this selection process, integrating diverse criteria and decision-making techniques. For instance, Hashemizadeh and Ju (2019) employed a Multi-Criteria Decision Making (MCDM) approach coupled with Geographic Information Systems (GIS) for project portfolio selection by construction contractors. Similarly, El-khalek et al. (2019) identified prequalification evaluation criteria for construction subcontractors, elucidating their influence on project success. Moreover, the use of analytical tools such as Partial Least Square Technique (PLS) has been advocated for assessing construction risks. In this context, this research aims to address the following objectives:

1. To review existing methodologies and frameworks for contractor selection in construction projects, with a focus on their strengths, limitations, and applicability.
2. To propose a comprehensive framework for contractor selection that integrates traditional methodologies, computational techniques, and expert systems.
3. To validate the proposed framework through case studies or simulations, demonstrating its effectiveness in improving decision-making processes in construction projects.

By achieving these objectives, this research seeks to contribute to the advancement of contractor selection practices in the construction industry, ultimately enhancing project success and performance.

1- METHODOLOGY

1.2. Conceptual Model

For a better understanding, this section presents a conceptual model of the process of designing, generating, and utilizing the proposed genetic fuzzy system for assessing credit risk among civil engineering contractors. The model is outlined in a step-by-step manner, as depicted in Figure 1.

The conceptual model illustrates the sequential steps involved in the proposed genetic fuzzy system, as follows:

1. **Data Collection**: The process begins with the collection of relevant data pertaining to credit risk assessment among civil engineering contractors. This data may include financial records, project histories, contractor qualifications, and other relevant information.
2. **Preprocessing**: The collected data undergoes preprocessing to clean and prepare it for analysis. This step may involve handling missing values, standardizing variables, and other data preprocessing techniques to ensure the quality and consistency of the data.
3. **Feature Selection**: Next, relevant features or variables for credit risk assessment are selected from the preprocessed data. This step involves identifying the most influential factors that contribute to credit risk among civil engineering contractors.
4. **Model Design**: The selected features are then used to design the genetic fuzzy system for credit risk assessment. This involves defining the structure of the fuzzy logic rules, membership functions, and genetic optimization algorithms that comprise the system.
5. **Training**: The designed genetic fuzzy system is trained using the preprocessed data. This step involves optimizing the system parameters and rule base using genetic algorithms to enhance its performance in credit risk assessment.
6. **Validation**: Once trained, the genetic fuzzy system is validated using independent datasets to assess its generalization and predictive accuracy. This step ensures that the system can effectively assess credit risk among civil engineering contractors in real-world scenarios.
7. **Deployment**: Finally, the validated genetic fuzzy system is deployed for practical use in assessing credit risk among civil engineering contractors. This may involve integrating the system into existing risk management frameworks or developing new tools for decision support in contractor selection processes.

By following these sequential steps outlined in the conceptual model, the proposed genetic fuzzy system can effectively assess credit risk among civil engineering contractors, thereby aiding in informed decision-making and risk management in construction projects.

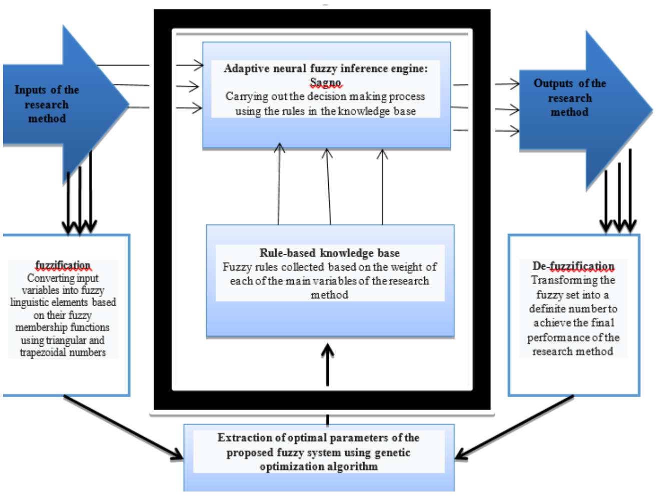


Fig. 1. Structure of the Proposed Research Methodology

As depicted in Figure 1, this research employs a proposed method utilizing genetic optimization algorithm for extracting optimal fuzzy rules and membership functions in training and generating the proposed research model.

2.2. Simulation of Fuzzy Genetic System

In the present study, the fuzzy genetic system is introduced for the first time in the field of research related to the assessment of credit risk of construction contractors. Considering the application of the designed fuzzy genetic system, a five-step process is considered for the design and simulation of this system for assessing the credit risk of construction contractors, which include:

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

After finalizing the conceptual model of the fuzzy genetic system, the input and output variables of this system are defined. In this step, for each input variable, membership functions are considered to convert crisp inputs to fuzzy ones and be placed in the fuzzy inference system. In this stage, the initial data of contractors including main and sub-components (economic component, skill and capability, technical, managerial, equipment, experience) required by the research are collected, evaluated, and categorized. These are then proposed as inputs for assessing credit risk and made available to the proposed fuzzy genetic system. The input and output variables of the research fuzzy genetic system for assessing the credit risk of construction contractors are visible in Figure 2.

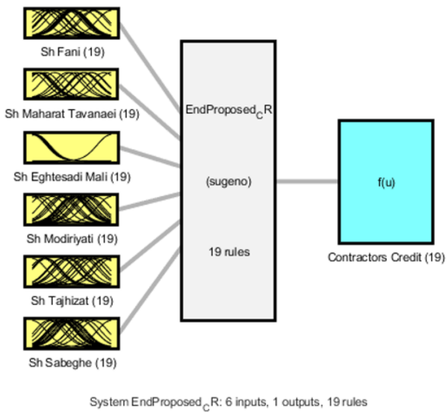


Figure 2: Linguistic Input and Output Variables of the Research Fuzzy Genetic System

Step 2: Definition of Linguistic Variables and Allocation of Numbers and Fuzzy Sets and Membership Functions to Them

To design the membership functions in the research fuzzy genetic system, the type of membership functions, components of each membership function, and the range of variation for each membership function must be determined. All the mentioned aspects necessary for designing the membership functions of the research fuzzy genetic system are designed by the genetic optimization algorithm. For linguistic variables (components of credit risk assessment for construction contractors) in the research fuzzy genetic system, the Gaussian membership function according to Equation (1) is used.

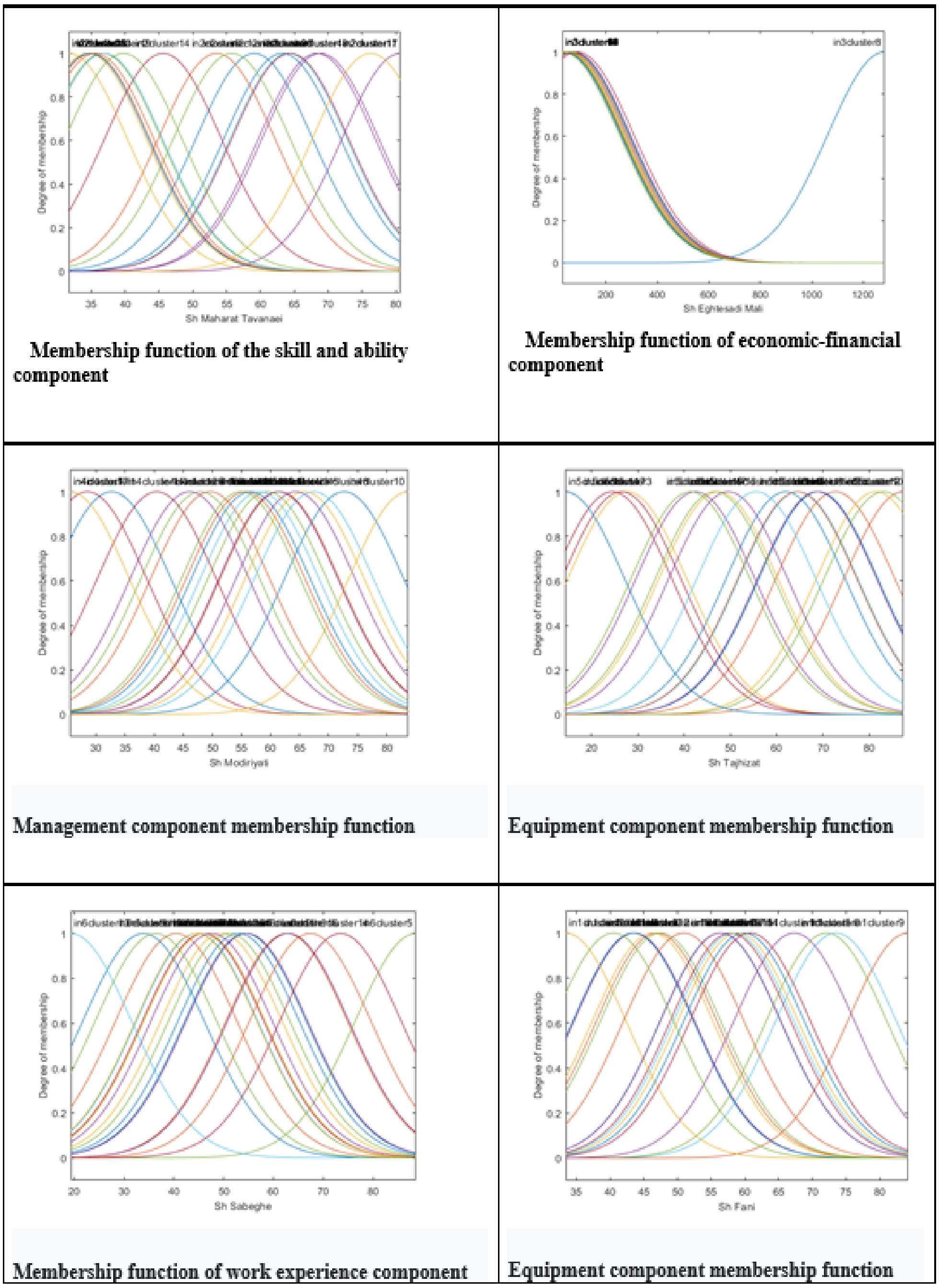
Equation (1)

$$f_1\ (\mathrm{x}) = \begin{cases} \exp\left[-\frac{1}{2} - \left(\frac{x-m_1}{\sigma_1}\right)^2\right], & x \leq m_1 \\ 1 & otherwise \end{cases}$$

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

$$\mu\ (\mathrm{x}) = f_1\ (\mathrm{x}) * f_2\ (\mathrm{x})$$

Figure 3 illustrates the proposed Gaussian membership functions in MATLAB environment for linguistic variables (components of credit risk assessment for construction contractors) in the research fuzzy genetic 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 for Construction Contractors) in the Research Fuzzy Genetic System

The questionnaire of this research, based on the credit evaluation components of contractors including technical, skill and capability, economic and financial, managerial and specialist staff, machinery, and past performance, will be designed as membership functions. These will be designed and provided to the specialized managers of reputable civil employer companies for completion, and the results will be used for training and testing the proposed fuzzy genetic system.

In Figure 3, the X-axis represents the values of each point of the membership functions, while the Y-axis represents the degree of membership (value) of each point on the X-axis, adjusted between 0 and 1. The selection of optimal membership functions along with their components plays a crucial role in the efficiency of each fuzzy inference, which in this research, optimal values of these components are extracted using the genetic optimization algorithm.

Step 3: Designing the Knowledge Base of the Research Fuzzy Genetic System

As mentioned, the knowledge base in fuzzy systems consists of a set of fuzzy rules. The fuzzy rules used in this thesis are Sugeno fuzzy rules, which consist of n antecedents and one consequent in the form of Equation (2).

Equation (2)

R_j :If X_1 is $A1_j$ and ... and Xn is An_j Then Construction Contractors Credi Cluster C_jt

As illustrated, X= [X_1, X_2,...,Xn]X=[X_1,X_2,...,Xn] represents an n-dimensional sample vector comprising the validation components of contractors. AijAij (where i=1,2,...,ni=1,2,...,n) denotes the initial linguistic values corresponding to the validation components of contractors. Cj signifies the label of the credit cluster for the contractor based on the Rj rule, serving as the consequent.

To formulate the knowledge base of the fuzzy genetic contractor system, a set of fuzzy rules in the following format (Equation 2) needs to be generated:

IF X_1 is A_{11} and X_2 is A_{21} and ... and X_n is A_{n1} THEN C_{1IF} X1 is A_{11} and X_2 is A_{21} and ... and Xn is A_{n1} THEN C1 IF X_1 is A_{12} and X_2 is A_{22} and ... and Xn is A_{n2} THEN C_{2IF} X_1 is A_{12} and X_2 is A_{22} and ... and Xn is A_{n2} THEN C2 ......

IF X_1 is A_{1m} and X_2 is A_{2m} and ... and Xn is Anm THEN C_{mIF} X_1 is A_{1m} and X_2 is A_{2m} and ... and Xn is A_{nm} THEN C_m

Initially, each attribute undergoes normalization within the range [0, 1]. Subsequently, the sample space is partitioned into subspaces, each associated with a fuzzy rule. The degree of compatibility of each sample Xp with the antecedent of a fuzzy rule is determined within the genetic fuzzy system, as described by Equation (3).

Equation (3)

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

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

Step 4: Development of the Inference Engine for the Genetic Fuzzy System

Within the genetic fuzzy system, the inference mechanism synthesizes the information gleaned from the fuzzy rules with the attributes of the sample under consideration to ascertain its appropriate cluster. A prevalent approach in fuzzy systems for inference is the single winner rule-based inference [21]. With this model, a new sample X_p= [X_{p1}, Xp_2,...,X_{pn}] is classified as depicted in Equation (4).

Equation (4)

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

The process of fuzzy inference within the genetic fuzzy system has been investigated [11], as illustrated in Figure 4. Furthermore, for the accurate evaluation of the genetic fuzzy model's performance, the center of gravity method has been adopted for defuzzification. Equation (5) delineates the defuzzification process of the genetic fuzzy model utilizing the center of gravity method.

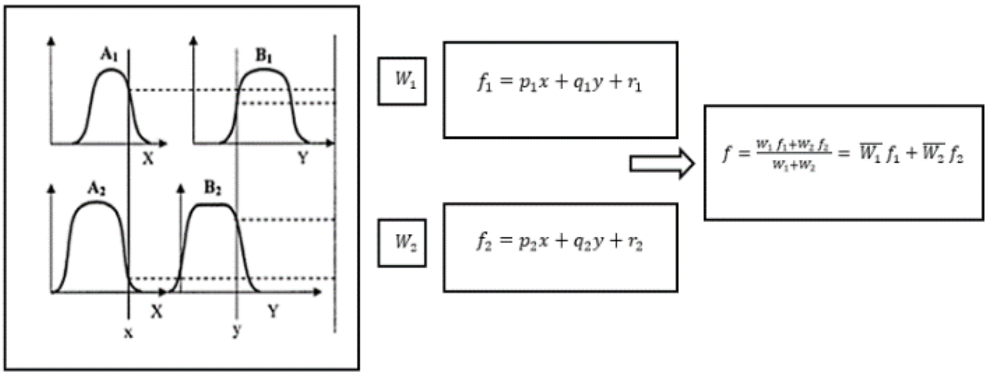


Fig. 4. How to infer fuzzy in the genetic fuzzy system of research[11].

Equation (5)

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

Step 5: Utilization of the Genetic Fuzzy System and Analysis of Outputs

The outputs generated by the genetic fuzzy system undergo both numerical and linguistic analyses to probe the dynamics of the output variable, "The degree of credibility of construction contractors," within the genetic fuzzy model. Figure 5 offers an in-depth examination of the behavior exhibited by both the input and output variables of the genetic fuzzy model.

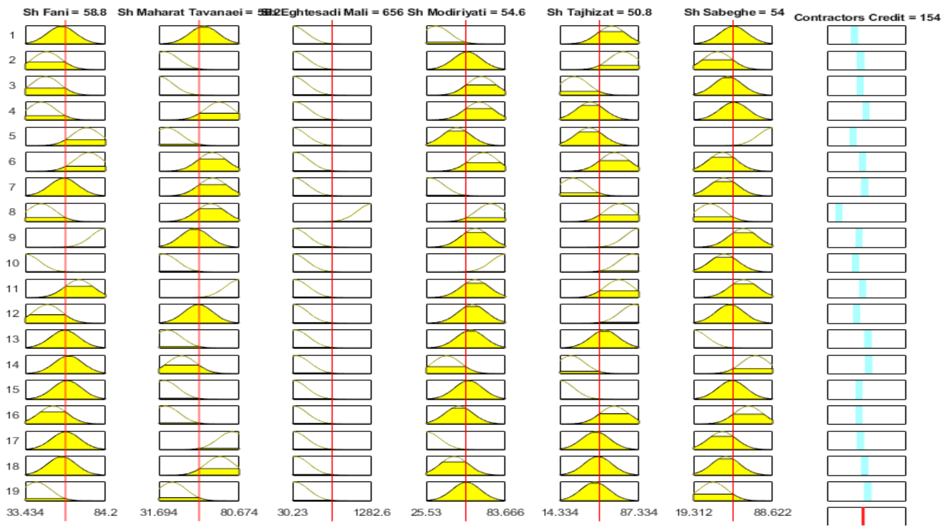
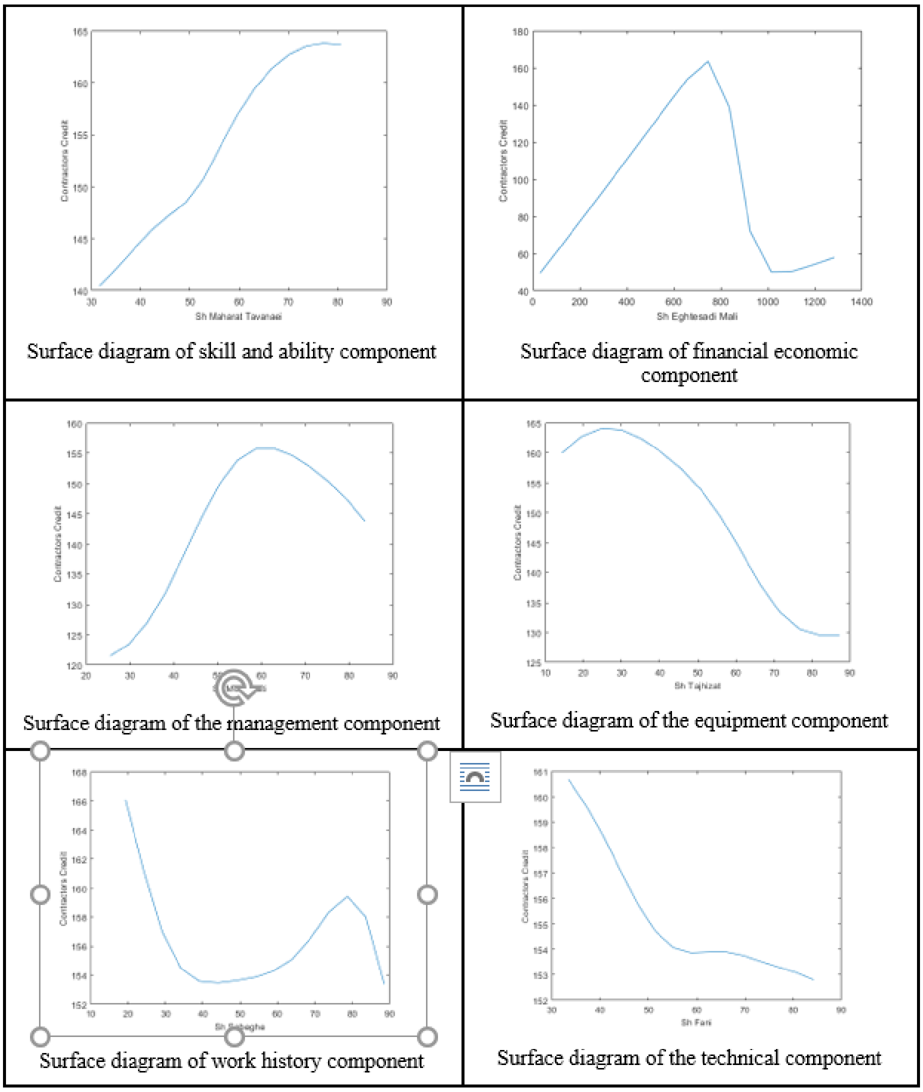


Fig. 5. Analysis of the Behavior of the Output Variable "Construction Contractors' Credibility" Numerically and Linguistically Based on Input Variables

The surface diagram of the fuzzy genetic model is derived using MATLAB software, employed during the design phase of this model. This visualization aids in comprehensively assessing the overall structure and functionality of the genetic fuzzy model developed for addressing the credit risk assessment challenge associated with 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

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

Figure 6 depicts a surface view showcasing the input and output components of the genetic fuzzy model utilized in the research.

In this visualization, the Y-axis represents the level of credibility attributed to contractors for receiving development projects, while the X-axis denotes the inputs of the genetic fuzzy system, namely the components utilized in measuring the credit risk associated with construction contractors.

Evaluation Metrics for Credit Risk Assessment of Civil Contractors

Various metrics have been utilized to evaluate the accuracy of credit risk assessment models for civil contractors. These metrics are calculated based on the actual and estimated risk values generated by credit risk assessment models for contractors. The most important metrics for calculating the accuracy of credit risk assessment for civil contractors are discussed below.

1. VAF Metric This metric is used to calculate the dispersion of actual credit risk levels of contractors compared to the estimated credit risk levels. Equation 5 is used to calculate the VAF metric [17].

Equation (6)

$$VAF = 1 - \left[\frac{var(\text{actual } Credit - Estimated\ Credit)}{var(\text{actual } Credit\ )}\right] * 100$$

High values of this metric indicate increased accuracy in the presented models for assessing the credit risk of civil contractors.

1. MARE Metric This metric is utilized to calculate the mean absolute error of credit risk assessment for civil contractors based on the actual assessment compared to the estimated credit risk levels. Equation 6 is presented to calculate the MARE metric [18].
   Equation (7)

$$MARE = mean\left[\frac{abs(actual \text{ Credit} - Estimated \text{ Credit})}{(actual \text{ Credit})}\right] * 100$$

   A lower value of this metric implies a reduction in the mean absolute error of credit risk assessment for civil contractors, accompanied by an increase in the accuracy of credit risk assessment for civil contractors.
1. VARE Metric This metric is used to calculate the dispersion of the absolute error of credit risk assessment for civil contractors. Equation 7 is used to compute this metric [13].

   Equation (8)

$$\text{VARE} = \text{var}\left[\frac{\text{abs(actual Credit} - \text{Estimated Credit)}}{\text{(actual Credit)}}\right] * 100$$

   As the value of this metric decreases, the presented models have a higher accuracy in assessing the credit risk of civil contractors.
1. MRE Metric This metric is used to calculate the magnitude of error in credit risk assessment for civil contractors based on the actual risk compared to the estimated risk. Equation 8 is utilized to compute this metric [20].
   Equation (9)

$$MRE = \left|\frac{(Actual \text{ Credit } - Estimated \text{ Credit})}{(Actual \text{ Credit})}\right|$$

   A lower value of this metric indicates a higher accuracy of the estimated credit risk for contractors in the model.
1. MMRE Metric the MMRE metric is used to calculate the average magnitude of error in credit risk assessment for civil contractors based on the actual risk compared to the estimated risk. Equation 9 is provided to compute the MMRE metric, which is necessary for measuring the average magnitude of error in credit risk assessment for civil contractors in credit risk assessment models for civil contractors [21].

   Equation (10):

$$\text{MMRE} = {}^{1}/_{\text{N}} \sum_{i=1}^{n} \text{MRE}_i$$

   A decrease in the value of this metric indicates an increase in the accuracy of credit risk assessment for civil contractors in the proposed model. Furthermore, using the metrics provided in this section, the extracted results of the research analysis are further examined and compared.

RESULTS AND DISCUSSION

In this section, we analyze the credit risk assessment of civil contractors in the analysis dataset using fuzzy genetic models, Rao_CCPQ, Li_OCICS, hierarchical analysis, and expert civil managers. We analyze the results in terms of the MRE, MMRE, VAF, VARE, and MARE metrics.

Using Equation 8, we can calculate the MRE (magnitude of error in credit risk assessment for civil contractors based on actual risk compared to estimated risk) in the fuzzy genetic model, Rao_CCPQ model, Li_OCICS model, and hierarchical analysis model for all civil contractors in the analysis dataset. The results of calculating the MRE values in these models for all civil contractors can be observed in Tables 1 to 4 and Figures 7 to 10.

Table 1: MRE values in the analysis dataset for the hierarchical analysis model

MRE	
Hierarchical analysis model	Contractor number
-0.20882	1
-0.22737	2
-0.28072	3
-0.09926	4

-0.07499	5
-0.04051	6
-0.05354	7
0.146799	8
0.274463	9
-0.08456	10
-0.0585	11
0.015	12
-0.1172	13
-0.11291	14
-0.00805	15
-0.06606	16
-0.04388	17
-0.1562	18
-0.07032	19
0.232152	20

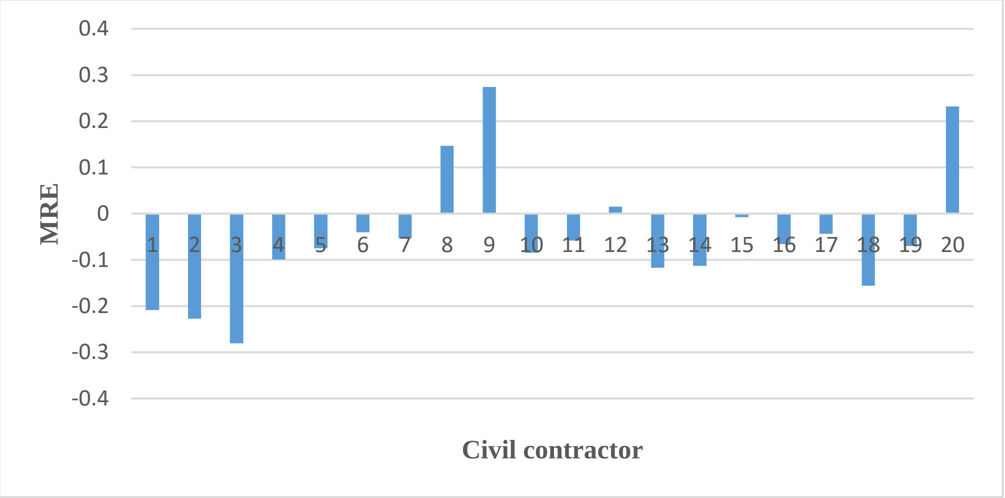


Figure 7- The amount of MRE in the analysis data set in the hierarchical analysis model

Table 2- The amount of MRE in the analysis data set in the Rao_CCPQ model

MRE	
Model Rao_CCPQ	Contractor number
-0.01302	1
-0.03434	2
0.043546	3
-0.01793	4
0.017243	5
-0.07783	6
0.040049	7
0.02984	8
0.013132	9
0.004785	10
-0.07464	11
-0.09931	12
0.00644	13

0.050797	14
0.05006	15
0.010224	16
-0.00339	17
0.011035	18
-0.03413	19
0.005412	20

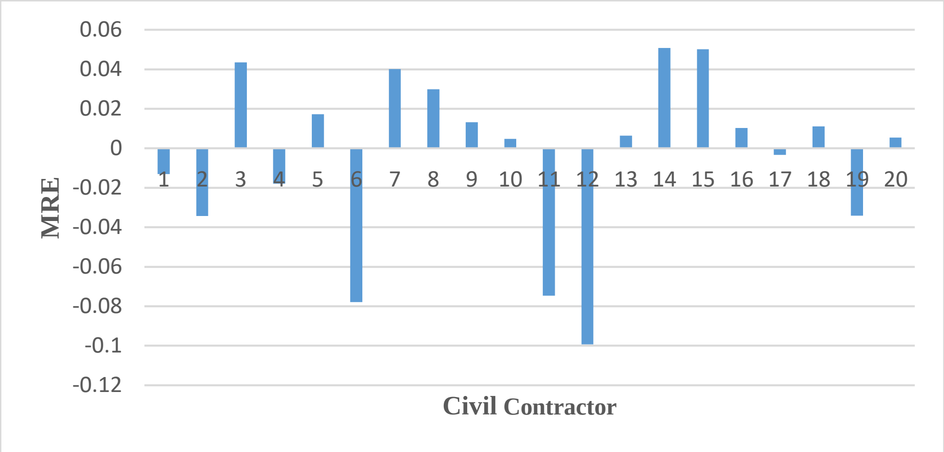


Figure 8- The amount of MRE in the analysis data set in the Rao_CCPQ model

Table 3: MRE Levels in the Analysis Dataset for the Li_OCICS Model

MRE	
Model Li_OCICS	Contractor number
-0.16648	1
-0.00996	2
-0.14086	3
-0.047	4
-0.19645	5
-0.08666	6
-0.16826	7
0.216306	8
0.215356	9
-0.25435	10
-0.37996	11
0.131667	12
-0.1172	13
-0.25429	14
0.031405	15
0.178211	16
0.086376	17
0.060245	18
0.136505	19
0.070035	20

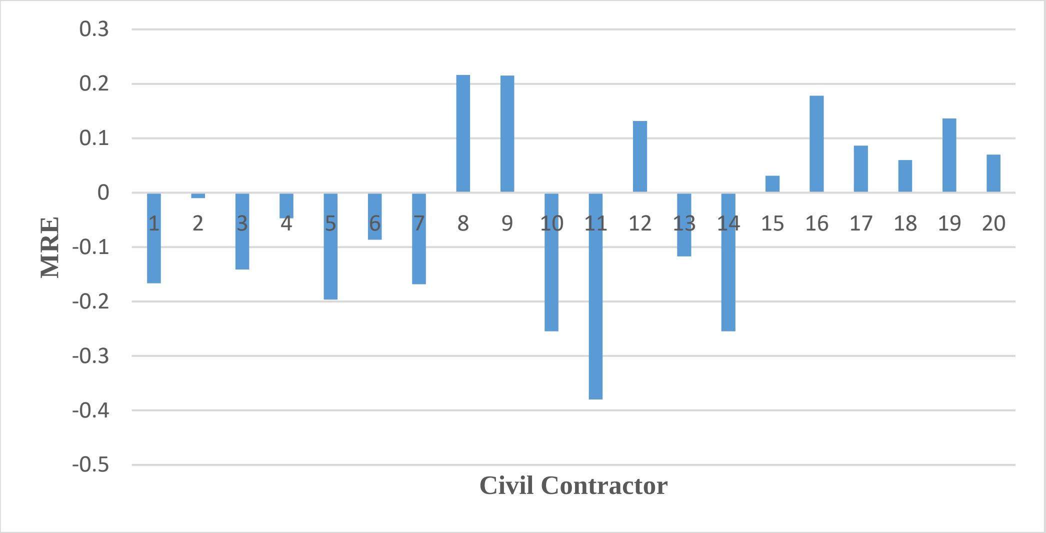


Figure 9: Comparison of MRE Levels in the Analysis Dataset for the Li_OCICS Model

Table 4: Comparison of MRE Levels for the Analysis Dataset in the Research Genetic Fuzzy Model

MRE	
Proposed Genetic Fuzzy Model	Contractor number
-0.02117	1
-0.05929	2
-0.01998	3
-0.0697	4
-0.08097	5
-0.04614	6
-0.07648	7
-0.05213	8
-0.07388	9
-0.06367	10
-0.11481	11
-0.05	12
-0.03783	13
-0.06059	14
-0.03946	15
-0.08724	16
-0.05583	17
-0.03607	18
-0.0515	19
-0.05894	20

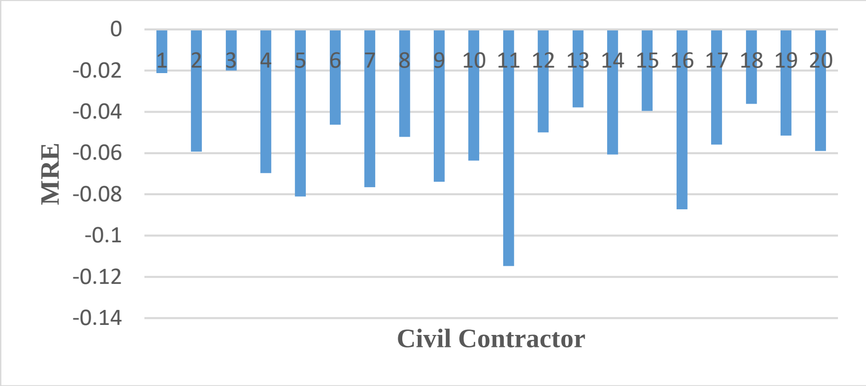


Figure 10: MRE Levels for the Analysis Dataset in the Research Genetic Fuzzy Model

For example, in Figures 7 to 10, it can be observed that the extracted MRE level for civil contractor number 10 in the research genetic fuzzy model is -0.06367. This value is lower compared to the compared models, namely, Rao_CCPQ, Li_OCICS, and hierarchical analysis, indicating an increase in accuracy in credit risk assessment for civil contractors in the research genetic fuzzy model, consistent with the opinions of expert civil managers. Table 5 and Figure 11 provide a comparison of MRE levels in the analysis dataset for the compared models.

Table 5: Comparison of MRE Levels in the Analysis Dataset for the Compared Models

MRE				Contractor number
Proposed Genetic Fuzzy Model	Rao_CCPQ	Hierarchical analysis model	Li_OCICS	
-0.02117	-0.01302	-0.20882	-0.16648	1
-0.05929	-0.03434	-0.22737	-0.00996	2
-0.01998	0.043546	-0.28072	-0.14086	3
-0.0697	-0.01793	-0.09926	-0.047	4
-0.08097	0.017243	-0.07499	-0.19645	5
-0.04614	-0.07783	-0.04051	-0.08666	6
-0.07648	0.040049	-0.05354	-0.16826	7
-0.05213	0.02984	0.146799	0.216306	8
-0.07388	0.013132	0.274463	0.215356	9
-0.06367	0.004785	-0.08456	-0.25435	10
-0.11481	-0.07464	-0.0585	-0.37996	11
-0.05	-0.09931	0.015	0.131667	12
-0.03783	0.00644	-0.1172	-0.1172	13
-0.06059	0.050797	-0.11291	-0.25429	14
-0.03946	0.05006	-0.00805	0.031405	15
-0.08724	0.010224	-0.06606	0.178211	16
-0.05583	-0.00339	-0.04388	0.086376	17
-0.03607	0.011035	-0.1562	0.060245	18
-0.0515	-0.03413	-0.07032	0.136505	19
-0.05894	0.005412	0.232152	0.070035	20

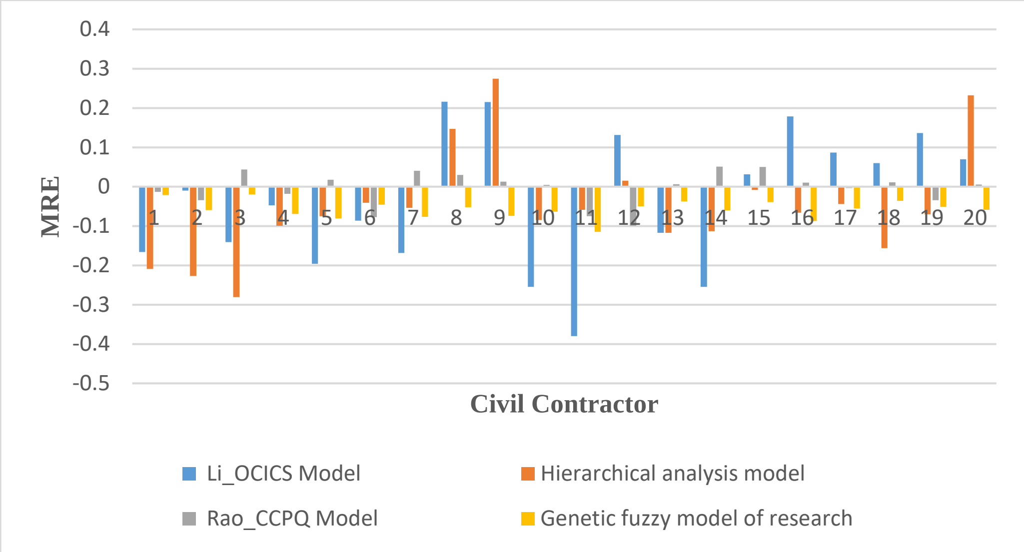


Figure 11: Comparison of MRE Levels in the Analysis Dataset for the Compared Models

As depicted in Figure 11, for the majority of civil contractors in the analysis dataset, the MRE considered in the research genetic fuzzy model shows less deviation compared to the models [28] Rao_CCPQ, [29] Li_OCICS, and hierarchical analysis [1], concerning the credit risk estimated by expert managers of civil contracting companies. Continuing with a focused analysis, the results of the mean error in credit risk assessment for civil contractors in the research genetic fuzzy model compared to models [28] Rao_CCPQ, [29] Li_OCICS, and hierarchical analysis [1] are extracted. This is presented as the MMRE metric, calculated using Equation 9, and can be observed in Table 6 and Figure 12.

Table 6: Comparison of MMRE Levels in the Analysis Dataset for the Compared Models

MMRE			
Hierarchical analysis model	Li_OCICS Model	Model Rao_CCPQ	Proposed Genetic Fuzzy Model
-0.05172	-0.03477	-0.0036	-0.05778

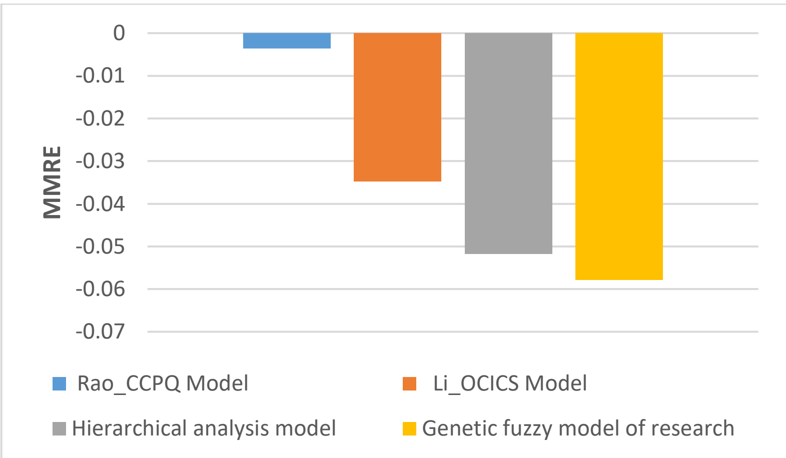


Figure 12: Comparison of MMRE Levels in the Analysis Dataset for the Compared Models

As depicted in Figure 12, the MMRE metric in the research genetic fuzzy model is -0.05778, which is lower compared to models [28] Rao_CCPQ, [29] Li_OCICS, and hierarchical analysis [1]. This lower value signifies the higher accuracy of the research genetic fuzzy model in credit risk assessment for civil contractors. Increased accuracy in credit risk assessment for civil contractors can ultimately assist in more confident project execution by contractors and, consequently, reduce the number of delayed or failed projects, which is the ultimate goal of the model proposed in this research.

Continuing, the results of the mean absolute error in credit risk assessment for civil contractors in the research genetic fuzzy model compared to models [28] Rao_CCPQ, [29] Li_OCICS, and hierarchical analysis [1] are extracted. This is presented as the MARE metric, calculated using Equation 6, and can be observed in Table 7 and Figure 13.

Table 7: Comparison of MARE Levels in the Analysis Dataset for the Compared Models

MARE			
Model Li_OCICS	Model Rao_CCPQ	Hierarchical analysis model	Fuzzy Genetic Model
0.719431	0.816892	0.075297	0.051055

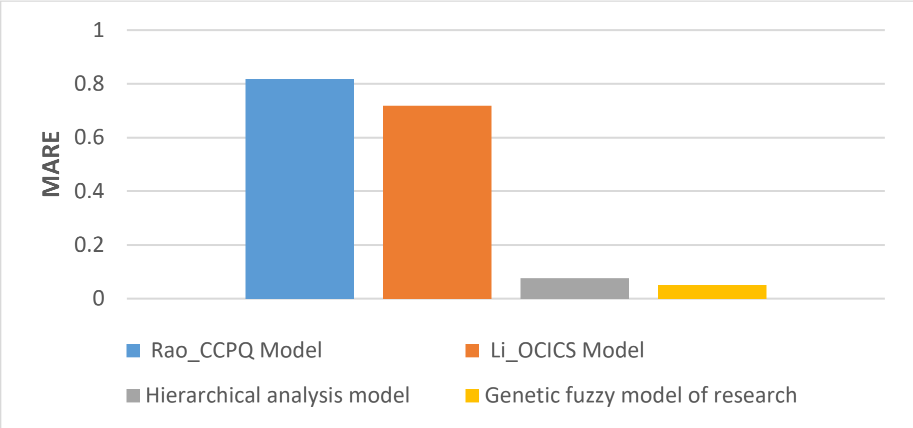


Figure 13: Comparison of MARE Levels in the Analysis Dataset for the Compared Models

As shown in Figure 13, the MARE metric in the research genetic fuzzy model is 0.051055, which is lower compared to models [28] Rao_CCPQ, [29] Li_OCICS, and hierarchical analysis [1]. This lower value indicates the higher accuracy of the research genetic fuzzy model in credit risk assessment for civil contractors.

Continuing, the results of the dispersion of the absolute error in credit risk assessment for civil contractors in the research genetic fuzzy model compared to models [28] Rao_CCPQ, [29] Li_OCICS, and hierarchical analysis [1] are extracted. This is presented as the VARE metric, calculated using Equation 7, and can be observed in Table 8 and Figure 14.

Table 8: Comparison of VARE Levels in the Analysis Dataset for the Compared Models

VARE			
Model Li_OCICS	Model Rao_CCPQ	Hierarchical analysis model	Proposed Genetic Fuzzy Model
0.719431	0.816892	0.075297	0.051055

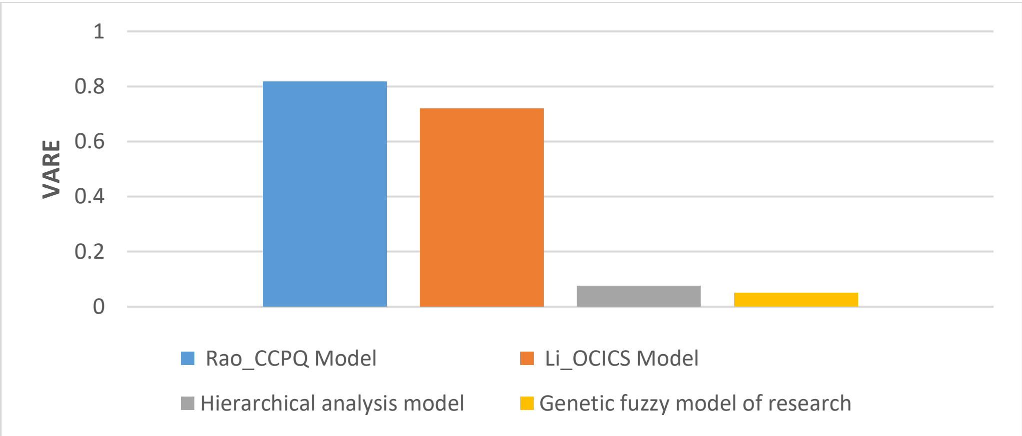


Figure 14: Comparison of VARE Levels in the Analysis Dataset for the Compared Models

As depicted in Figure 14, the VARE metric in the research genetic fuzzy model is 0.051055, which is lower compared to models [28] Rao_CCPQ, [29] Li_OCICS, and hierarchical analysis [1]. This lower value indicates the higher accuracy of the research genetic fuzzy model in credit risk assessment for civil contractors.

Continuing, the results of the dispersion of the actual credit risk assessment for civil contractors compared to the estimated credit risk in the research genetic fuzzy model compared to models [28] Rao_CCPQ, [29] Li_OCICS, and hierarchical analysis [1] are extracted. This is presented as the VAF metric, calculated using Equation 5, and can be observed in Table 9 and Figure 15.

Table 9: Comparison of VAF Levels in the Analysis Dataset for the Compared Models

VAF			
Model Li_OCICS	Model Rao_CCPQ	Hierarchical analysis model	Proposed Genetic Fuzzy Model
-144.715	-178.708	-9.72965	-2.21642

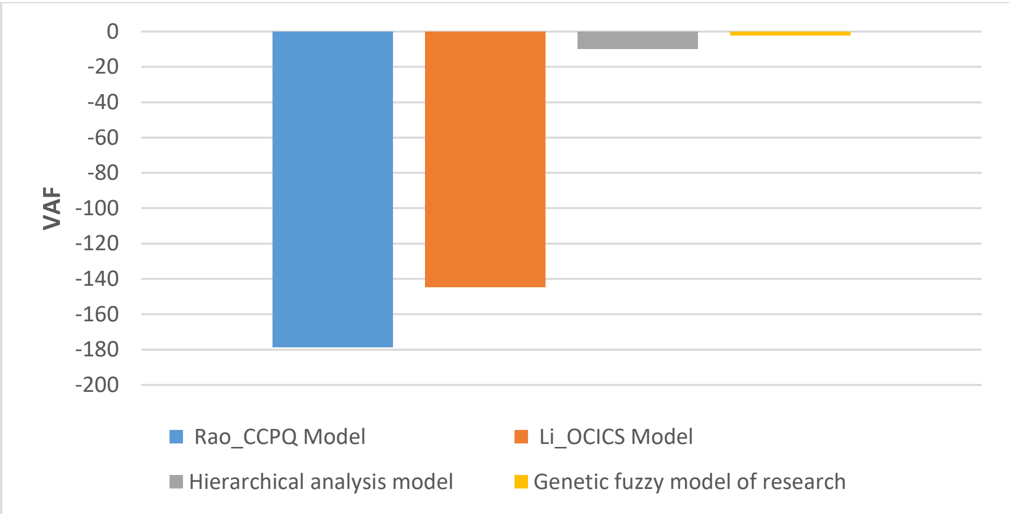


Figure 15: Comparison of VAF Levels in the Analysis Dataset for the Compared Models

As shown in Figure 15, the VAF metric in the research genetic fuzzy model is -2.21642, which is higher compared to models [28] Rao_CCPQ, [29] Li_OCICS, and hierarchical analysis [1]. This higher value indicates the greater accuracy of the research genetic fuzzy model in credit risk assessment for civil contractors.

In Table 10, the mean and standard deviation of the research genetic fuzzy model and the compared models are extracted and presented using SPSS software.

Table 10: Mean and Standard Deviation of the Research Genetic Fuzzy Model and Compared Models

Descriptive Statistics

	N	**Mean**	**Std. Deviation**	**Minimum**	**Maximum**
Hierarchical analysis model	20	55.7500	6.01117	45.10	64.10
Model Rao_CCPQ	20	53.7448	6.94777	46.72	67.48
Model Li_OCICS	20	54.6000	5.66150	45.10	63.10
Proposed Genetic Fuzzy Model	20	56.6836	7.29736	45.34	72.67

To assess the significance of the accuracy level in evaluating the credit risk of civil contractors across the compared models and rank these models, we need to examine the results presented in Table 11.

Table 11: Examination of the significance of the accuracy level in evaluating the credit risk of civil contractors across the compared models and ranking these models.

Ranks	
	Mean Rank
Hierarchical analysis model	2.73
Model Rao_CCPQ	1.85
Model Li_OCICS	2.43
Proposed Genetic Fuzzy Model	3.00

Table 11 presents the average rank of each of the compared models by the SPSS software. Comparing the average ranks shows that the highest average rank (3.00) belongs to the Fuzzy Genetic Model, indicating that the accuracy level in evaluating the credit risk of civil contractors is higher in this model compared to other compared models. Following the Fuzzy Genetic Model, the highest accuracy in evaluating the credit risk of civil contractors in the compared models includes the Analytic Hierarchy Process model, model [29] Li_OCICS, and model [28] Rao_CCPQ, respectively.

Table 12 is the most important Friedman test table, which should be evaluated before interpreting Tables 10 and 11. If the Friedman test is significant, we should then proceed to interpret the results of the descriptive tables and average ranks. Table 12 represents the statistical significance in the research analysis. The P-value obtained by the SPSS software in the research analysis is 0.032, which is less than the significance level of 0.05. A significance level of less than 0.05 (0.05 P <) indicates the statistical significance of the Friedman test in the research analysis, meaning that the ranking of models for evaluating the credit risk of civil contractors is meaningful.

Table 12: Results of the Friedman test in the research analysis.

Test Statistics[a]	
N	20
Chi-Square	8.789
df	3
Asymp. Sig.	.032
a. Friedman Test	

As shown in Table 12, the Friedman test indicates that the accuracy and ranking of evaluating the credit risk of civil contractors differ among the compared research models.

In the following section, the analysis of the findings is focused on comparing the Fuzzy Genetic Model, which utilizes genetic optimization algorithms for extracting rules and optimal membership functions, with other models for extracting optimal fuzzy system parameters.

The research findings regarding the accuracy of the Fuzzy Genetic Model in assessing the credit risk of civil contractors compared to other algorithms for extracting optimal fuzzy rules, including the Ishibuchi algorithm [30], Ishibuchi and Genetic algorithm [31], Rao algorithm and Particle Swarm Optimization [36], IVFS model [32], SGERD model [33], Target model [34], and GNP model [35], are examined using metrics such as MRE, MMRE, VAF, VARE, and MARE, as well as the Friedman test. Using Equation 8, the MRE (Mean Relative Error, measuring the credit risk assessment error of civil contractors based on actual risk compared to estimated risk) in the Fuzzy Genetic Model and the aforementioned comparison models for all civil contractors in the dataset are calculated. The results of calculating the MRE levels in these models are presented in Table 13.

Table 13: Comparison of MRE levels in the Fuzzy Genetic Model compared to other models for extracting optimal fuzzy system parameters

MRE								
Elragal _PSO Model	**Proposed genetic fuzzy model**	IsBu_GA Model	IsBu Model	GNP Model	SGERD Model	IVFS Model	Model Target	**Contractor number**
-0.10585078	-0.14819	-0.23287323	-0.21170294	-0.29638411	-0.16936235	-0.02117029	-0.14819206	1
-0.09882057	-0.19764	-0.35575935	-0.09882204	-0.27670172	-0.19764408	-0.15811527	-0.11858645	2
-0.01998001	-0.07992	-0.13986014	-0.15984016	-0.05994006	-0.15984016	-0.15984016	-0.05994006	3
-0.03486117	-0.26131	-0.10452597	-0.017421	-0.017421	-0.19163095	-0.017421	-0.17420996	4
-0.06072934	-0.04049	-0.34415742	-0.02024455	-0.08097822	-0.12146733	-0.12146733	-0.20244554	5
-0.09228175	-0.41528	-0.34606866	-0.27685493	-0.18456995	-0.27685493	-0.18456995	-0.11535622	6
-0.09560281	-0.03824	-0.15296367	-0.03824092	-0.21032505	-0.03824092	-0.03824092	-0.07648184	7
-0.05212545	-0.27803	-0.29540557	-0.19114478	-0.15639119	-0.22589838	-0.0173768	-0.10426079	8
-0.05910161	-0.2512	-0.13299051	-0.17732068	-0.07388362	-0.14776724	-0.04433017	-0.05910689	9
-0.10611735	-0.21224	-0.19101791	-0.25469055	-0.14856949	-0.1697937	-0.12734528	-0.04244843	10
-0.06888324	-0.29849	-0.20664952	-0.25257164	-0.2755327	-0.04592212	-0.11480529	-0.11480529	11
-0.06666274	-0.13333	-0.15	-0.25	-0.15	-0.18333333	-0.06666667	-0.06666667	12
-0.09454159	-0.30246	-0.26465028	-0.09451796	-0.07561437	-0.18903592	-0.15122873	-0.05671078	13
-0.10098983	-0.24238	-0.04039588	-0.3029691	-0.16158352	-0.12118764	-0.02019794	-0.16158352	14
-0.01972923	-0.25645	-0.2761777	-0.17754281	-0.25645072	-0.07890791	-0.09863489	-0.23672374	15
-0.03489597	-0.29661	-0.05234323	-0.17447744	-0.05234323	-0.08723872	-0.03489549	-0.05234323	16
-0.07444195	-0.18607	-0.18607421	-0.27911131	-0.22328905	-0.14885937	-0.0930371	-0.20468163	17

-0.07214815	-0.32468	-0.09018759	-0.07215007	-0.05411255	-0.16233766	-0.09018759	-0.12626263	18
-0.03426422	-0.17235	-0.20682523	-0.25853154	-0.03447087	-0.20682523	-0.10341262	-0.05170631	19
-0.02946296	-0.19159	-0.0736898	-0.04421388	-0.01473796	-0.04421388	-0.02947592	-0.13264163	20

As evident from Table 13, for the majority of civil contractors in the dataset analyzed, the MRE considered in the comparison models exhibits less deviation in the Fuzzy Genetic Model compared to Ishibuchi algorithm [30], Ishibuchi and Genetic algorithm [31], Rao algorithm and Particle Swarm Optimization [36], IVFS model [32], SGERD model [33], Target model [34], and GNP model [35] concerning the credit risk perceived by specialist managers of civil employer companies.

Table 14 and Figure 16 compare the levels of MMRE, VAF, VARE, and MARE in the Fuzzy Genetic Model compared to other models for extracting optimal fuzzy system parameters.

Table 14: Comparison of MMRE, VAF, VARE, and MARE levels in the Fuzzy Genetic Model compared to other models for extracting optimal fuzzy system parameters.

Method	Evaluation metrics			
	MMRE	**VARE**	**VAF**	**MARE**
SGERD	-0.14831809	0.409661217	-24.20001	0.409661217
GNP	-0.14016497	0.869330542	-42.56779	0.869330542
Target	-0.11525768	0.898774139	-47.59507	0.898774139
IVFS	-0.08462097	0.936163288	-51.20499	0.936163288
Elragal	-0.06607454	0.96260364	-54.87854	0.96260364
IsBu_GA	-0.19213079	0.300292234	-13.64215	0.300292234
Proposed Genetic Fuzzy Model	-0.21635	0.088443	-3.27949	0.088443
IsBu	-0.16761841	0.339039841	-19.109104	0.339039841

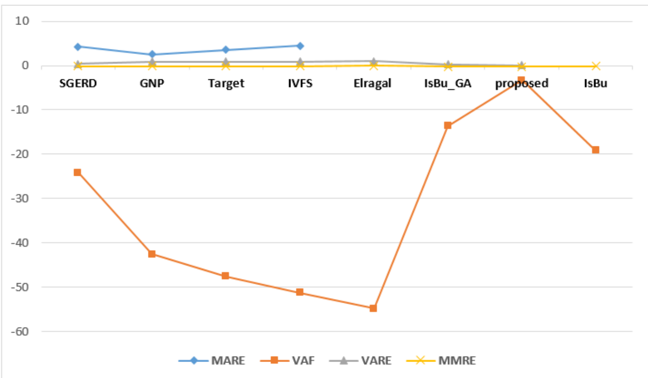


Figure 16: Comparison of MMRE, VAF, VARE, and MARE levels in the Fuzzy Genetic Model compared to other models for extracting optimal fuzzy system parameters.

As depicted in Figure 16, the VAF metric in the Fuzzy Genetic Model research is -3.27949, which is higher compared to Ishibuchi algorithm [30], Ishibuchi and Genetic algorithm [31], Rao algorithm and Particle Swarm Optimization [36], IVFS model [32], SGERD model [33], Target model [34], and GNP model [35]. This higher value indicates a higher accuracy of the Fuzzy Genetic Model in assessing the credit risk of civil contractors.

Furthermore, as shown in Figure 16, the MMRE, VARE, and MARE metrics in the Fuzzy Genetic Model are -0.21635, 0.088443, and 0.088443 respectively. These values are lower compared to Ishibuchi algorithm [30], Ishibuchi and Genetic algorithm [31], Rao algorithm and Particle Swarm Optimization [36], IVFS model [32], SGERD model [33], Target model [34], and GNP model [35]. This lower value indicates a higher accuracy of the Fuzzy Genetic Model in assessing the credit risk of civil contractors.

Table 15 presents the mean and standard deviation in the Fuzzy Genetic Model compared to other models for extracting optimal fuzzy system parameters, extracted and presented by the SPSS software.

Table 15: Mean and standard deviation in the Fuzzy Genetic Model compared to other models for extracting optimal fuzzy system parameters.

Descriptive Statistics					
	N	**Mean**	**Std. Deviation**	**Minimum**	**Maximum**
IsBu	20	62.3840	8.02546	50.40	79.67
IsBu_GA	20	63.5840	7.05937	51.51	76.67
IVFS	20	57.9342	6.17878	48.24	70.67
Target	20	59.6840	7.44737	48.34	76.85
GNP	20	60.7340	5.95715	51.34	72.67
SGERD	20	61.4840	7.97633	45.55	77.67
Proposed Genetic Fuzzy Model	20	65.1342	9.38714	51.40	84.67
ElrPSO	20	57.0335	6.53484	46.55	71.67

To assess the significance of the accuracy in evaluating the credit risk of civil contractors in the models for extracting optimal fuzzy system parameters and ranking these models, we need to examine the results presented in Table 16.

Table 16: Examination of the significance of the accuracy in evaluating the credit risk of civil contractors in the models for extracting optimal fuzzy system parameters and ranking these models.

Ranks	
	Mean Rank
IsBu	5.23
IsBu_GA	5.93
IVFS	3.10
Target	3.93
GNP	4.35
SGERD	5.15
Proposed Genetic Fuzzy Model	6.13
ElrPSO	2.20

In Table 16, the average rank of each of the compared models for extracting optimal fuzzy system parameters is provided by the SPSS software. Comparing these average ranks reveals that the highest average rank (6.13) is assigned to the Fuzzy Genetic Model research, indicating that the accuracy level in evaluating the credit risk of civil contractors in this model is higher than in the other compared models.

Following the Fuzzy Genetic Model research, the highest accuracy in evaluating the credit risk of civil contractors in the compared models includes Ishibuchi and Genetic algorithm [31], Ishibuchi algorithm [30], SGERD model [33], GNP model [35], Target model [34], IVFS model [32], and Rao algorithm and Particle Swarm Optimization.

Table 17 is the most important Friedman test table for this section, which should be evaluated before interpreting Tables 15 and 16. If the Friedman test is significant, we should then proceed to interpret the results of the descriptive tables and average ranks. Table 17 demonstrates the statistical significance in the research analysis.

The P-value obtained by the SPSS software in the research analysis for this section is 0.000 (zero), which is less than the significance level of 0.05. A significance level of less than 0.05 (0.05 P <) indicates the statistical significance of the Friedman test in the research analysis for this section, meaning that the ranking of models for evaluating the credit risk of civil contractors in the models for extracting optimal fuzzy system parameters is meaningful.

Table 17: Results of the Friedman test in the research analysis.

Test Statistics[a]	
N	20
Chi-Square	44.985
df	7
Asymp. Sig.	.000
a. Friedman Test	

As evident from Table 17, the Friedman test indicates that the accuracy and ranking of evaluating the credit risk of civil contractors by the models for extracting optimal fuzzy system parameters proposed in the research are significantly different from each other.

The results suggest that the proposed model in this article attempts to select the best contractors considering all relevant criteria. After executing the comparative models and the Fuzzy Genetic Model research in the MATLAB environment, various metrics including MRE, MMRE, VAF, VARE, and MARE were extracted from these models and compared and analyzed using provided graphs. The results indicate an improvement in these metrics in the Fuzzy Genetic Model research compared to the compared models. This improvement will enhance the accuracy of credit risk assessment for civil contractors.

CONCLUSION

In conclusion, the evaluation of credit risk assessment models for civil contractors presented in this study has provided valuable insights into the effectiveness of different methodologies. Through rigorous analysis of numerical data extracted from various models, including the Fuzzy Genetic Model, Rao_CCPQ, Li_OCICS, and hierarchical analysis, several important conclusions can be drawn.

Firstly, the Fuzzy Genetic Model demonstrates superior performance across multiple evaluation metrics compared to the other models. The model exhibits lower Mean Relative Error (MRE), Mean of Mean Relative Error (MMRE), Mean Absolute Error (MARE), and Variance of Absolute Error (VARE), indicating higher accuracy and precision in credit risk assessment for civil contractors.

Furthermore, the comparison of these metrics across different models highlights the consistent advantage of the Fuzzy Genetic Model. The model consistently outperforms others in terms of minimizing errors and maximizing accuracy, as evidenced by statistical tests such as the Friedman test, which confirms the significance of these differences.

The practical implications of these findings are significant. By adopting the Fuzzy Genetic Model for credit risk assessment, civil contracting companies can make more informed decisions, leading to improved project outcomes and reduced financial risks. The higher accuracy of the Fuzzy Genetic Model can enable contractors to identify and mitigate potential risks more effectively, ultimately enhancing project execution and reducing the likelihood of delays or failures.

In conclusion, this study underscores the importance of utilizing advanced modeling techniques, such as the Fuzzy Genetic Model, for credit risk assessment in the civil contracting industry. The findings provide valuable guidance for industry practitioners and researchers seeking to enhance risk management practices and improve project performance.

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